

Sentinel-1 SAR-Based Flood Extent Mapping and Impact Assessment in Kogi State, Nigeria: A Google Earth Engine Application of the 2022 Flood Event

Gwamzhi Ponsah Emmanuel, Dr. Omomoh Emmanuel, Titus James Tumba, Zubairu Monica & Agahiu Justice Oneh

ARTICLE INFORMATION

Article history:

Published: August 2026

Keywords:

Sentinel-1
 Synthetic Aperture Radar
 Flood Mapping
 Google Earth Engine
 Kogi State
 Nigeria
 Damage Assessment

ABSTRACT

Flooding remains Nigeria's most recurrent and destructive natural hazard, and the September–October 2022 flood event was among the most severe in the country's recorded history, with Kogi State, sited at the confluence of the Niger and Benue Rivers, among the worst affected areas in the country. This study applies the UN-SPIDER Recommended Practice for flood mapping and damage assessment, implemented in Google Earth Engine (GEE), to delineate the extent and impact of the 2022 flood across Kogi State using Sentinel-1 Synthetic Aperture Radar (SAR) imagery. A dual change-detection approach, combining a multi-year (2017–2022) dry-season backscatter baseline anomaly with a conventional before/after ratio threshold, was used to capture both riverbank overflow and inland ponding. VH-polarised Ground Range Detected (GRD) images were speckle-filtered, and permanent water bodies and steep terrain were masked out using the JRC Global Surface Water dataset and the HydroSHEDS Digital Elevation Model, respectively. The resulting flood layer was intersected with ESA WorldCover land-cover classes and WorldPop gridded population data to quantify exposure, and further reclassified into a four-class severity zonation for the worst-affected local government area. The analysis identified approximately 6,388 km² of inundated land across the state, including roughly 1,014 km² of cropland and 115 km² of built-up area, with an estimated 1.03 million people located within flood-classified pixels. These SAR-derived estimates are broadly consistent with field-verified figures reported by Nigeria's National Emergency Management Agency and with independently published local flood studies for Kogi State. The results demonstrate the technical feasibility of an automated, cloud-based, near-real-time flood-mapping and damage-assessment system for Nigeria and provide a replicable template for institutionalisation within the National Space Research and Development Agency (NASRDA).

1. Introduction

Flooding is among the most destructive natural hazards worldwide, and its increasing frequency and severity have been linked to climate change, extreme precipitation, rapid urbanisation and inadequate drainage infrastructure (Intergovernmental Panel on Climate Change [IPCC], 2023). Flood disasters constitute the most frequent and economically damaging category of natural hazard confronting Nigeria, and their frequency, severity and geographic extent have increased markedly over the past decade (National Space Research and Development Agency [NASRDA], 2026). The 2022 rainy season produced the most catastrophic flood event in the country since 2012, affecting 33 of Nigeria's 36 states and the Federal Capital Territory and killing more than 600 people (Al Jazeera, 2022), with the National Emergency Management Agency, National Bureau of Statistics and United Nations Development Programme (NEMA, NBS, & UNDP, 2023) confirming that the floods affected roughly 4.4 million people nationally, displaced approximately 1.4 million, and damaged over 200,000 homes and more than 332,000 hectares of farmland. The disaster was driven by unusually intense rainfall combined with the controlled release of excess water from the Lagdo Dam in Cameroon into the Benue River system (Busari & Adebayo, 2022); an independent remote-sensing assessment found that national flood extent rose by roughly 300% following the Lagdo release, from about 50,000 ha in July–August to approximately 200,000 ha by September, with some 105,000 people nationally estimated at critical risk of riverine flooding (Abu & Ibebuchi, 2025).

Among the thirty-six states, Kogi was one of the most severely affected. Situated at the Niger–Benue confluence, the state experienced flooding described by its governor as a “humanitarian tragedy,” with Ibaji Local Government Area reported almost entirely submerged and eight further riverine local government areas affected (Floodlist, 2022). A subsequent NEMA/NBS/UNDP (2023) household survey found that around seventy percent of Kogi households reported an adverse flood impact, the highest of six states assessed. Notably, national impact tallies are not fully consistent across sources: whereas NEMA, the NBS and UNDP (2023) reported roughly 4.4 million people affected and 1.4 million displaced, another contemporaneous review put the national toll at approximately seven million affected and two million displaced (Olukayode, 2023), a divergence symptomatic of the wider data and methodological gap between developed- and developing-country flood research (Sibandze et al., 2024) and of the absence of a single, standardised, satellite-based accounting system of the kind proposed by NASRDA (2026). Geospatial risk-mapping exercises covering all thirty-six states have consistently placed Kogi among the states with the highest concentration of high-risk local government areas (Njoku et al., 2020), underscoring its value as a pilot case for an operational SAR-based flood-mapping capability.

Nigeria has historically lacked a standardised, operational system for producing timely, nationally consistent flood-extent and damage information (NASRDA, 2026). Conventional assessments rely heavily on optical satellite imagery, compromised by cloud cover during the very periods when flooding occurs, or on slow field surveys that cannot support emergency situational awareness. Synthetic Aperture Radar (SAR) overcomes this limitation because it operates at microwave wavelengths that penetrate cloud cover regardless of daylight, making it the preferred sensor for flood detection in tropical, cloud-prone environments (Torres et al., 2012). The Copernicus Sentinel-1 mission provides freely available, globally consistent C-band SAR imagery at approximately 10 m resolution with a short revisit interval, and its integration with cloud-computing platforms has substantially lowered the barrier to operational flood mapping (DeVries et al., 2020).

Google Earth Engine (GEE) has become the platform of choice for this purpose because it hosts petabyte-scale, analysis-ready archives of Sentinel-1, Sentinel-2 and ancillary datasets and performs the computation on Google's servers rather than the analyst's own hardware (DeVries et al., 2020). Building on this, the UN Office for Outer Space Affairs, through its UN-SPIDER programme, has published a Recommended Practice for Flood Mapping and Damage Assessment Using Sentinel-1 SAR Data in Google Earth Engine, providing a standardised workflow for SAR change detection and for intersecting the resulting flood layer with population, cropland and built-up datasets (UN-SPIDER Knowledge Portal, n.d.). This workflow has since been applied and validated elsewhere, including in Bangladesh (Uddin et al., 2019) and, most recently, for the 2024 Chiang Rai flood in Thailand, where it achieved 93.38% classification accuracy against ground-truth data (Thammaboribal et al., 2025). Threshold-based change detection of the kind used here remains the most widely deployed approach for operational SAR flood mapping, though convolutional neural network (CNN) classifiers trained directly on Sentinel-1 imagery have recently shown promise as a more automated alternative (Tavus et al., 2022). This study operationalises the UN-SPIDER Recommended Practice, as adapted within a broader national flood-mapping proposal developed by NASRDA (2026), to map the extent, cropland and urban exposure, population exposure, and graded inundation severity associated with the 2022 flood event in Kogi State. The specific objectives are to: (i) delineate the SAR-derived flood extent using a dual change-detection approach; (ii) quantify affected cropland and built-up area using ESA WorldCover; (iii) estimate exposed population using WorldPop; (iv) generate a reclassified flood-severity zonation for the worst-affected local government area; and (v) evaluate the consistency of these estimates against field-reported figures and selected published Kogi State flood studies, thereby assessing the feasibility of a national flood-intelligence system.

2. Study Area

Kogi State lies in Nigeria's North Central zone, between approximately latitudes 7°30' and 8°N and longitudes 5°30' and 7°E, covering about 29,833 km² (Fatoye, 2018; Wikipedia, 2026). Nicknamed the “Confluence State,” it is the only state bordering ten others, and its capital, Lokoja, sits precisely where the River Niger meets the River Benue before the combined flow continues south toward the Niger Delta (Kogi State Government, 2024; Figure 1). This position places the state directly in the path of floodwaters generated far upstream on both rivers, including Lagdo Dam releases on the Benue.

The state experiences a tropical wet-and-dry climate with a single rainy season from roughly April to October and a dry season from November to March (Kogi State Government, 2024). Peak rainfall, together with upstream dam releases, typically occurs between August and October, coinciding with maximum discharge at the confluence and with the period during which the most damaging floods, including 2012 and 2022, have occurred.

Geologically, the western half of the state is underlain by the crystalline Precambrian Basement Complex, while the eastern half is underlain by Cretaceous-to-Recent sedimentary formations of the Anambra and southern Bida basins (Fatoye, 2018). Quaternary alluvial deposits line the Niger and Benue floodplains, and it is these low-lying terraces, rather than the elevated uplands, that form the seasonally inundated land captured in this study's SAR-derived flood layer.

Demographically, Kogi recorded 3,314,043 people at the 2006 census, with a 2022 estimate of approximately 4,466,800 across twenty-one local government areas and three main ethno-linguistic groups — Igala, Ebira and Okun (Fatoye, 2018; Wikipedia, 2026). Floodplain agriculture (rice, yam, cassava, maize) is central to the rural economy, which is also why the riverine local government areas are simultaneously the most agriculturally productive and the most flood-exposed.

Nine local government areas along the Niger and Benue — Lokoja, Kogi (headquartered at Koton-Karfe), Ajaokuta, Ofu, Igalamela-Odolu, Bassa, Idah, Ibaji and Omala — were identified by the state government as the primary zones affected in 2022, with Ibaji almost completely submerged (Floodlist, 2022). This combination of low-lying topography, dense riverine settlement and exposure to two major river systems makes Kogi both highly flood-vulnerable and an instructive case study.

This vulnerability is corroborated by prior geospatial research. A statewide multi-criteria hazard–vulnerability model classified 4.71% of Kogi as very-high flood risk and 15.26% as high risk, with Lokoja, Koton-Karfe, Bassa and Ibaji exhibiting the highest hazard index (Aladejana & Ebijuoworih, 2024). At the community scale, 161 of 256 sampled communities (62.9%) along the Niger–Benue corridor were found vulnerable, with riverbank communities in Ajaokuta at highest risk (Ozim et al., 2021), while vulnerability along the Benue was shown to concentrate within roughly six kilometres of the river bank (Umaru & Adedokun, 2020). Within individual catchments, an AHP-based assessment of the Ofu River catchment found 163.07 km² and 392.63 km² in very-high- and high-risk zones respectively, exposing an estimated 66,700 people (Alfa et al., 2018), and comparable LGA-level inundation shares of roughly a quarter of the land area have been documented elsewhere in the state (Oluyomi et al., 2024). Focusing specifically on the September 2022 event, a flood hazard mapping study integrating rainfall, elevation, land-use/land-cover, soil characteristics, vegetation and drainage-density indicators identified the same riverine local government areas as the most hazard-prone (Adewara & Olapeju, 2025). These sub-state studies, though methodologically distinct, consistently corroborate the concentration of flood risk along the Niger–Benue corridor that the present study's own results (Section 4) also identify.

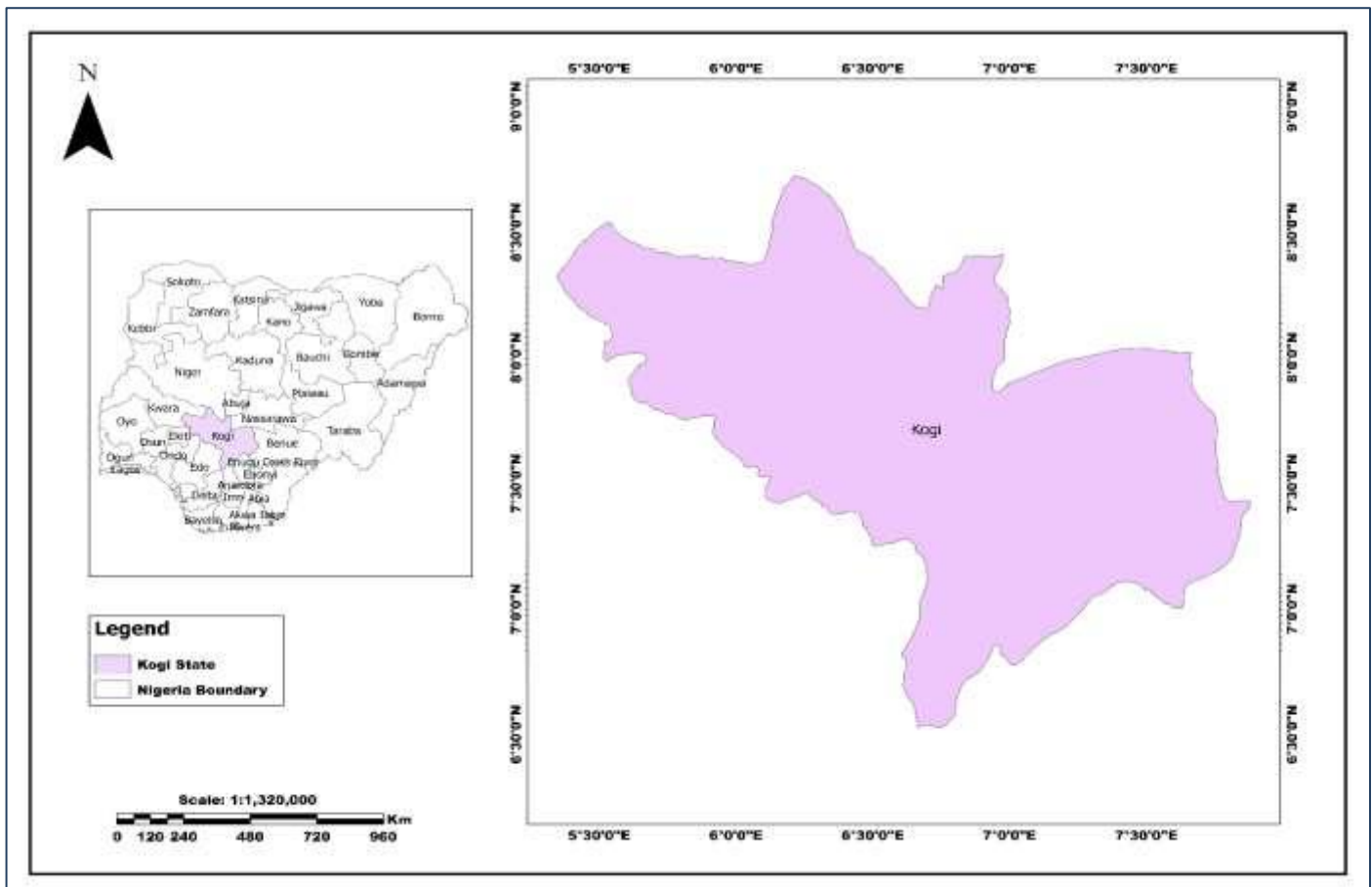


Figure 1. Location map of Kogi State within Nigeria, showing the state boundary relative to the national boundary and geographic coordinate grid.

3. Methodology

The methodological approach adheres to the UN-SPIDER Recommended Practice (UN-SPIDER Knowledge Portal, n.d.), enhanced by combining two independent SAR change-detection techniques to improve flood-layer reliability, following the broader logic of temporal-anomaly-based detection algorithms developed for GEE (DeVries et al., 2020). All processing was executed within the GEE JavaScript code editor using analysis-ready Sentinel-1 GRD imagery.

3.1 Data Sources

Table 1 summarises the datasets used. Sentinel-1 SAR imagery (IW mode, VH polarisation, 10 m resolution) formed the primary input (Torres et al., 2012). A cloud-free Sentinel-2 dry-season (Jan–Apr 2022) true-colour composite provided visual context. The JRC Global Surface Water dataset (Pekel et al., 2016) masked permanent open water, the HydroSHEDS DEM (Lehner et al., 2008) derived slope to exclude steep terrain, the ESA WorldCover 10 m 2021 v200 product (Zanaga et al., 2022) identified cropland and built-up classes, and the WorldPop 100 m gridded population dataset (Tatem, 2017) estimated population exposure.

Dataset	Source / Product	Resolution	Role in Analysis
SAR imagery	Sentinel-1 GRD, IW mode, VH polarisation	10 m	Pre-/post-flood backscatter change detection
Optical imagery	Sentinel-2 SR Harmonized, dry-season composite	10 m	True-colour reference base map
Surface water	JRC Global Surface Water, occurrence layer	30 m	Masking of permanent river channels
Elevation / slope	WWF HydroSHEDS DEM	~90 m	Exclusion of steep terrain (slope $\geq 8^\circ$)
Land cover	ESA WorldCover 10 m 2021 v200	10 m	Cropland / built-up class identification
Population	WorldPop gridded population, 2020	100 m	Population within flood extent

Table 1. Satellite and ancillary datasets used in the SAR flood-mapping workflow.

3.2 Pre-processing and Speckle Filtering

The Sentinel-1 GRD collection was filtered to IW mode, VH polarisation and 10 m resolution, then clipped to Kogi State. A pre-flood window (1 May–10 July 2022) and a post-flood window (1 August–31 October 2022, spanning peak discharge) were mosaicked separately, and a circular focal-mean speckle filter (50 m radius) was applied to both, consistent with UN-SPIDER guidance (UN-SPIDER Knowledge Portal, n.d.).

3.3 Dual Change-Detection Flood Extraction

Two complementary methods were combined. A multi-year dry-season baseline anomaly method computed mean VH backscatter for March–July across 2017–2022 as a stable reference, classifying pixels more than 1.5 dB darker than baseline as flooded — effective for riverbank overflow. A conventional before/after ratio method, following the UN-SPIDER protocol, classified pixels exceeding a pre/post ratio of 1.05 as flooded — effective for discrete inland ponding. The two binary layers were combined by logical union to reduce omission error.

Permanent water was removed using the JRC Global Surface Water occurrence layer (pixels >95% historical occurrence excluded as the permanent channel; Pekel et al., 2016), and steep terrain, unreliable for SAR backscatter, was masked using HydroSHEDS-derived slope, excluding all pixels above 8° (Lehner et al., 2008).

3.4 Impact and Exposure Assessment

The refined flood layer was overlaid with ESA WorldCover to isolate flood-affected cropland and built-up area (Zanaga et al., 2022), and with WorldPop 2020 to estimate population within flood-classified pixels (Tatem, 2017). Zonal statistics were computed for the whole state using GEE's reduceRegion at 100 m scale, yielding the four headline indicators reported in Section 4.

3.5 Flood Severity Zonation

To add a graded severity dimension for the worst-affected locality, the SAR-derived inundation surface for Kogi Local Government Area (Koton-Karfe; land area $\approx 1,498 \text{ km}^2$) was reclassified in a GIS environment into four ordinal classes — low (0–15%), mild (15–30%), high (30–50%) and very high (>50%) — following the multi-criteria hazard-zonation logic used elsewhere in the state (Aladejana & Ebijuoworih, 2024). The resulting surface (Figure 3) and its area statistics (Table 4) complement the binary state-wide extent in Table 2 and allow comparison with the SAR-based inundation extent independently reported for the same locality by Isiaka et al. (2023).

4. Results and Discussion

The dual change-detection analysis identified extensive flooding across Kogi State. Table 2 summarises the headline indicators, and Figure 2 shows the Sentinel-2 true-colour composite with the SAR-derived flood extent, affected cropland and affected urban area overlaid, alongside the auto-generated statistics panel and legend.

Indicator	Value	Unit
Total flood extent	6,388.28	km ²
Affected cropland	1,013.72	km ²
Affected urban area	114.60	km ²
Estimated population within flood extent	1,030,091	persons

Table 2. Sentinel-1 SAR-derived flood impact statistics for Kogi State, 2022 flood event.

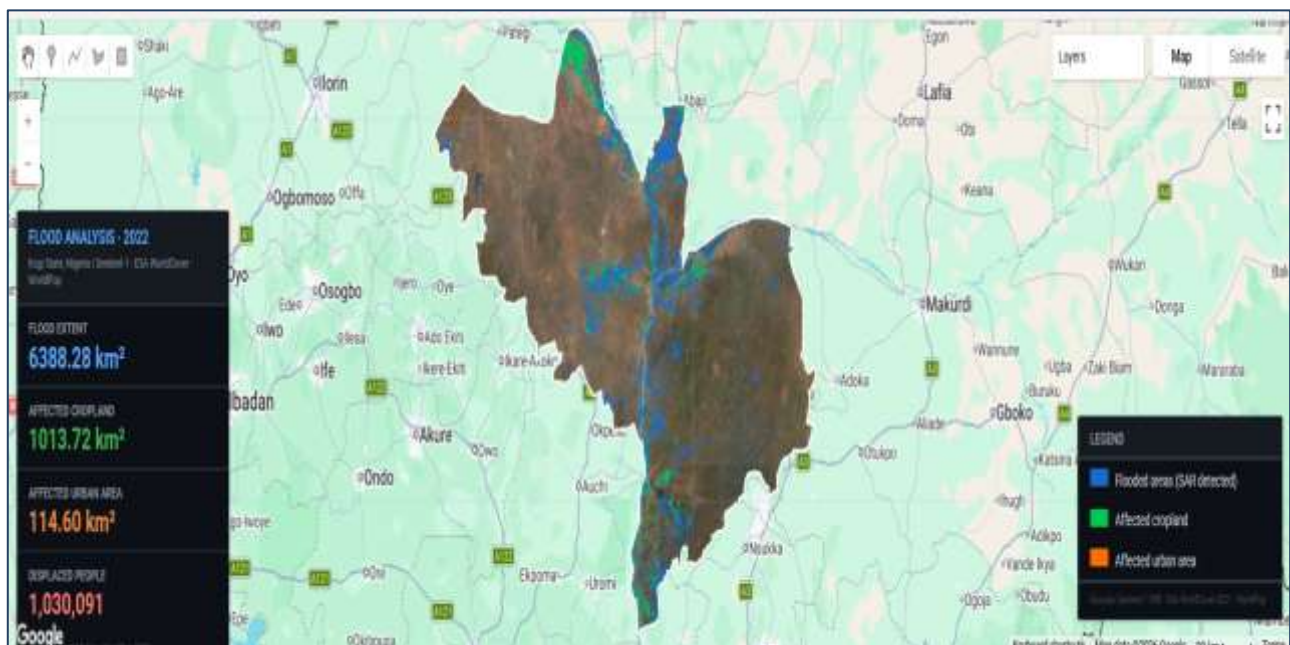


Figure 2. GEE output showing Sentinel-1 SAR-derived flood extent (blue), affected cropland (green) and affected urban area (orange) over Kogi State, overlaid on a Sentinel-2 dry-season composite, with the computed statistics panel and legend.

The mapped flood extent (Figure 2) is concentrated along the Niger and Benue corridors, forming two inundation belts converging at Lokoja — consistent with independent Landsat- and MODIS-based observations showing floodwater spreading from the confluence into southern Kogi and northern Anambra (NASA Earth Observatory, 2022), with ground reports that Ibaji was almost entirely submerged (Floodlist, 2022), and with the six-kilometre river-proximity vulnerability corridor identified along the Benue by Umaru and Adedokun (2020).

At the locality scale, a Sentinel-1 assessment of the same event in Koton-Karfe (Kogi LGA) recorded 198.255 km² inundated at the 13 October 2022 peak, with mapped urban area falling from 220.902 km² in May to 87.473 km² in November — a loss exceeding 133 km² (Isiaka et al., 2023). This locality-level urban loss alone exceeds the 114.60 km² of built-up area classified as flood-affected across the entire state in this study (Table 2), suggesting the present state-wide urban estimate, based on a single VH-polarisation pass, may understate localised urban inundation. A separate multi-year GEE time series for the confluence area found peak coverage of only 172.68 km² in 2018, declining to 99.12 km² by 2023 (Ohunene et al., 2025); the much larger extent found here for 2022 confirms it was an anomalous outlier year, consistent with the national dam-driven surge reported by Abu and Ibebuchi (2025).

The 1,013.72 km² ($\approx$ 101,372 ha) of flooded cropland is a substantial share of national losses, given NEMA/NBS/UNDP's (2023) estimate of roughly 332,000 ha affected across six states surveyed, and is consistent with Kogi recording the highest proportion of affected households ($\approx$ 70%) among those states.

The estimated 1.03 million people within SAR-classified flood pixels exceeds NEMA's field-verified displacement figures for Kogi, part of a national total of roughly 1.4 million displaced (Busari & Adebayo, 2022; NEMA, NBS, & UNDP, 2023), and the narrower national estimate of 105,000 people at critical riverine risk (Abu & Ibebuchi, 2025). This is conceptually expected: the SAR figure measures exposure (all residents whose grid cell coincides with a flood-classified pixel), not confirmed displacement, and the static 2020 WorldPop layer cannot capture pre-emptive evacuation or partial inundation effects. The consistent order of magnitude across these independent measures nonetheless supports the overall scale of impact identified here.

Figure 3 presents the reclassified severity zonation for Kogi LGA described in Section 3.5, and Table 4 summarises the corresponding statistics. Of the $\approx$ 294.59 km² classified — roughly a fifth of the LGA's 1,498 km² — 111.93 km² (38.0%) fell in the low class, 112.79 km² (38.3%) in mild, 55.39 km² (18.8%) in high, and 14.47 km² (4.9%) in very high. The combined mild-to-very-high area of $\approx$ 182.66 km² is broadly consistent, in order of magnitude, with the 198.255 km² peak inundation extent independently reported for the same locality by Isiaka et al. (2023), providing reasonable external support for the severity zonation despite differing classification methods and acquisition dates.

Severity Class	Area (km ²)	Share of Classified Area (%)
Low (0–15%)	111.93	38.0
Mild (15–30%)	112.79	38.3
High (30–50%)	55.39	18.8
Very High (>50%)	14.47	4.9
Total classified area	294.59	100.0

Table 4. Area statistics for the reclassified flood-severity zonation of Kogi Local Government Area, 2022.

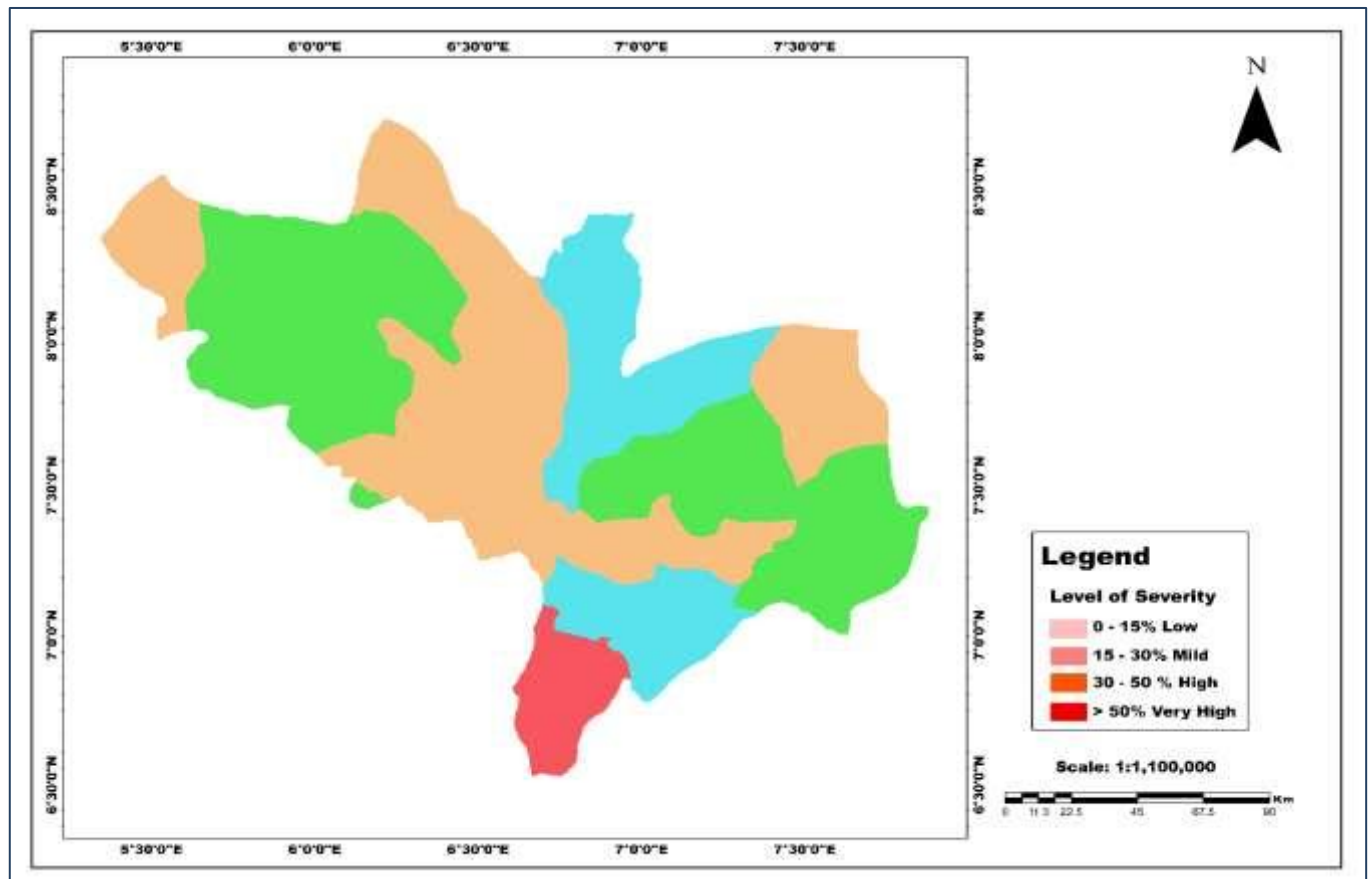


Figure 3. Reclassified flood-severity zonation of Kogi Local Government Area (Koton-Karfe), classifying inundated land into low, mild, high and very-high severity classes.

Table 3 compares the SAR-derived state-wide indicators with available field-reported figures. A fully reconciled, LGA-level validation dataset was not available at the time of writing, but the broad correspondence between the two independent sources supports the credibility of the workflow and illustrates its central value: unlike field surveys, which lag an event by weeks to months, the SAR-based approach can generate a defensible, quantified flood-impact assessment within hours, at national scale, without dependence on cloud-free conditions.

Impact Indicator	SAR-Derived Estimate (This Study)	Field-Reported Figure (NEMA / NBS-UNDP)
Flood extent / affected area	6,388.28 km ² (state-wide)	9 riverine LGAs affected; Ibaji ~100% submerged
Affected cropland	1,013.72 km ² (~101,372 ha)	~332,000 ha nationally (6 states surveyed)
Population exposed / displaced	~1,030,091 (exposure)	~1.4 million displaced nationally; ~70% of Kogi households affected
Households affected in Kogi	Not directly estimated	~70% of surveyed households affected (highest of 6 states)

Table 3. Comparison of SAR-derived exposure estimates with field-reported impact figures for Kogi State and Nigeria, 2022 (values not directly equivalent; see discussion for conceptual differences).

Overall, the results confirm that a dual change-detection SAR workflow in GEE, following the UN-SPIDER Recommended Practice, can reproduce the general magnitude and spatial pattern of a major flood disaster using only free satellite data and cloud computing, without optical imagery or extensive field mobilisation, and that its outputs align with independently published Kogi State flood-risk research spanning several methods and scales — the central justification for institutionalising the approach within NASRDA (2026).

5. Conclusion

This study applied a Sentinel-1 SAR change-detection workflow, implemented in Google Earth Engine and grounded in the UN-SPIDER Recommended Practice, to map the extent, impact and graded severity of the September–October 2022 flood in Kogi State. Combining a multi-year dry-season backscatter baseline anomaly with a before/after ratio threshold captured both riverbank overflow and inland ponding, producing a flood-extent layer of approximately 6,388 km² affecting an estimated 1,014 km² of cropland, 115 km² of built-up area and over one million people (Table 2, Figure 2), together with a reclassified severity zonation for the worst-affected local government area (Table 4, Figure 3). These figures are broadly consistent with field-reported statistics from NEMA, the NBS and UNDP, and with independently published Kogi State flood-risk research, while illustrating the specific value satellite-based monitoring adds: rapid, cloud-independent, nationally consistent information generated within hours rather than weeks. The findings support the technical and operational feasibility of the National Flood Mapping and Damage Assessment System proposed for Nigeria.

6. Recommendation

Building on these findings, the following recommendations are proposed:

- Field validation. Future applications should be validated against ground-truth points, high water marks, or very-high-resolution imagery to quantify accuracy and refine detection thresholds for Nigeria's hydro-climatic conditions.
- Adaptive, dual-polarisation thresholding. Incorporating VV and VH polarisation and adaptive thresholding (e.g., Otsu), or exploring CNN-based classifiers trained directly on Sentinel-1 imagery (Tavus et al., 2022), in place of fixed thresholds would likely improve accuracy across varied land-cover and terrain conditions, and help address the localised urban-detection shortfall highlighted by comparison with independent local-scale SAR studies in Section 4.
- Refinement of population exposure estimates. Exposure figures should be clearly distinguished from field-verified displacement, and where possible supplemented with dynamic population layers and social-vulnerability indicators such as index-based approaches (Oyedele et al., 2022) or the VARI Flood framework (Fox et al., 2024).
- Integration with multi-criteria hazard–vulnerability zonation. The SAR outputs demonstrated here should be paired with multi-criteria hazard–vulnerability frameworks, as developed for Kogi State by Aladejana and Ebijuworih (2024), rather than treated as a purely physical hazard measure.
- Participatory and community-level data. Bottom-up, community-verified vulnerability information, collected through Participatory GIS as demonstrated for Lokoja by Buba et al. (2021), should complement the top-down SAR workflow to improve local relevance and support evacuation planning.
- National scale-up and institutionalisation. The workflow should be extended to all flood-prone states and river basins and embedded as a standing operational capability within NASRDA, consistent with the parent national proposal (NASRDA, 2026).
- Historical flood archive and early warning. A systematic, multi-year archive of SAR-derived flood layers, of the kind piloted for the confluence area by Ohunene et al. (2025), should be built and linked to NEMA's emergency protocols and national hydrological forecasting to support flood-frequency analysis and anticipatory warning.

References

- [1] Abu, I.-O., & Ibebuchi, C. (2025). Risk assessment of the 2022 Nigerian flood event using remote sensing products and climate data. *Remote Sensing*, 17(11), Article 1814. <https://doi.org/10.3390/rs17111814>
- [2] Adewara, B., & Olapeju, O. (2025). Flood hazard mapping of Kogi State, Nigeria: The case of September 2022. *IRASS Journal of Arts, Humanities and Social Sciences*, 2(3), 101–106.
- [3] Al Jazeera. (2022, October 17). Nigeria flood death toll tops 600 as thousands evacuated. <https://www.aljazeera.com/news/2022/10/17/nigeria-flood-death-toll-rises-as-thousands-evacuated>

- [4] Aladejana, O., & Ebijuoworih, E. J. (2024). Flood risk assessment in Kogi State, Nigeria through the integration of hazard and vulnerability factors. *Discover Geoscience*, 2(1). <https://doi.org/10.1007/s44288-024-00036-y>
- [5] Alfa, M., Ajibike, M. A., & Daffi, R. (2018). Application of Analytic Hierarchy Process and Geographic Information System techniques in flood risk assessment: A case of Ofu River catchment in Nigeria. *Journal of Degraded and Mining Lands Management*, 5(4). <https://doi.org/10.15243/jdmlm.2018.054.1363>
- [6] Buba, F. N., Ojinnaka, O. C., Ndukwe, R., Agbaje, G., & Orofin, Z. O. (2021). Assessment of flood vulnerability in some communities in Lokoja, Kogi State, Nigeria, using Participatory Geographic Information Systems. *International Journal of Disaster Risk Reduction*. <https://doi.org/10.1016/j.ijdrr.2021.102111>
- [7] Busari, S., & Adebayo, B. (2022, October 13). Nigeria floods: Hundreds killed and more than 1.4 million displaced. CNN. <https://www.cnn.com/2022/10/13/africa/hundreds-killed-nigeria-floods-intl/index.html>
- [8] DeVries, B., Huang, C., Armston, J., Huang, W., Jones, J. W., & Lang, M. W. (2020). Rapid and robust monitoring of flood events using Sentinel-1 and Landsat data on the Google Earth Engine. *Remote Sensing of Environment*, 240, Article 111664. <https://doi.org/10.1016/j.rse.2020.111664>
- [9] Fatoye, F. B. (2018). Geology and mineral resources of Kogi State, Nigeria. *International Journal of Multidisciplinary Sciences and Engineering*, 9(7), 7–13.
- [10] Floodlist. (2022, October 4). Nigeria – Floods in Kogi “humanitarian tragedy” says governor. <https://floodlist.com/africa/nigeria-floods-kogi-october-2022>
- [11] Fox, S., Agyemang, F. S. K., Hawker, L., & Neal, J. (2024). Integrating social vulnerability into high-resolution global flood risk mapping. *Nature Communications*, 15. <https://doi.org/10.1038/s41467-024-47394-2>
- [12] Intergovernmental Panel on Climate Change. (2023). Climate change 2023: Synthesis report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC.
- [13] Isiaka, I., Ajadi, S. A., Arowolo, S. A., Mustapha, S. O., Ndukwe, K., & Oluoma, C. C. (2023). Flood impact assessment in Koton Karfe using Sentinel-1 Synthetic Aperture Radar (SAR) data. *International Journal of Environment and Geoinformatics*. <https://doi.org/10.30897/ijegeo.1348753>
- [14] Kogi State Government. (2024). History. <https://kogistate.gov.ng/history/>
- [15] Lehner, B., Verdin, K., & Jarvis, A. (2008). New global hydrography derived from spaceborne elevation data. *Eos, Transactions American Geophysical Union*, 89(10), 93–94. <https://doi.org/10.1029/2008EO100001>
- [16] National Emergency Management Agency, National Bureau of Statistics, & United Nations Development Programme. (2023). Nigeria flood impact, recovery and mitigation assessment report 2022–2023. UNDP Nigeria. <https://www.undp.org/sites/g/files/zskgke326/files/2023-12/nigeriafloodimpactrecoverymitigationassessmentreport2023.pdf>
- [17] National Space Research and Development Agency. (2026). National flood mapping and damage assessment system for Nigeria using Sentinel-1 SAR and Google Earth Engine (GEE) [Unpublished project proposal]. NASRDA.
- [18] NASA Earth Observatory. (2022, October 13). Flooding inundates southern Nigeria. NASA Science. <https://science.nasa.gov/earth/earth-observatory/flooding-inundates-southern-nigeria-150463/>
- [19] Njoku, C. G., Efiog, J., & Ayara, N.-A. N. (2020). A geospatial expose of flood-risk and vulnerable areas in Nigeria. *International Journal of Applied Geospatial Research*, 11(3). <https://doi.org/10.4018/ijagr.20200701.oa1>
- [20] Ohunene, I., Adewuyi, T., Garba, A., Mbow, C., Agbaje, G., Rufus, O., & Monsor, O. (2025). Assessing nature-based flood mitigation measures at the general area of the confluence of Rivers Benue and Niger in Kogi State, Nigeria. *American Journal of Remote Sensing*. <https://doi.org/10.11648/j.ajrs.20251301.12>
- [21] Olukayode, O. M. (2023). Preview of causes, frequency, extent, magnitude and intensity of flooding in Nigeria. *IIARD International Journal of Geography and Environmental Management*, 9(2), 52–60. <https://doi.org/10.56201/ijgem.v9.no2.2023.pg52.60>
- [22] Oluyomi, H. O., Ojo, A. G., Amanabo, U. H., Imhanfidon, J. O., Kopteer, E. P., Peter, E. S., Ezeanya, P. I., Areh, M. O., Monica, O. N., Emmanuel, D. N., & Nwabughigou, V. C. (2024). Assessment of flood occurrence and vulnerability in Kabba/Bunu local government area, Kogi State, Nigeria. *World Journal of Advanced Research and Reviews*, 23(1). <https://doi.org/10.30574/wjarr.2024.23.1.2277>
- [23] Oyedele, P., Kola, E., Olorunfemi, F., & Walz, Y. (2022). Understanding flood vulnerability in local communities of Kogi State, Nigeria, using an index-based approach. *Water*, 14(17), Article 2746. <https://doi.org/10.3390/w14172746>
- [24] Ozim, C., Olufemi, O. S., Ekpo, A., Alamaeze, N. K., & Mbanaso, M. U. (2021). GIS based analysis of Niger-Benue River flood risk and vulnerability of communities in Kogi State, Nigeria. *European Journal of Environment and Earth Sciences*. <https://doi.org/10.24018/ejgeo.2021.2.5.187>
- [25] Pekel, J.-F., Cottam, A., Gorelick, N., & Belward, A. S. (2016). High-resolution mapping of global surface water and its long-term changes. *Nature*, 540(7633), 418–422. <https://doi.org/10.1038/nature20584>
- [26] Sibandze, P., Kalumba, A. M., Aljaddani, A. H., Zhou, L., & Afuye, G. (2024). Geospatial mapping and meteorological flood risk assessment: A global research trend analysis. *Environmental Management*. <https://doi.org/10.1007/s00267-024-02059-0>
- [27] Tatem, A. J. (2017). WorldPop, open data for spatial demography. *Scientific Data*, 4, Article 170004. <https://doi.org/10.1038/sdata.2017.4>
- [28] Tavus, B., Can, R., & Kocaman, S. (2022). A CNN-based flood mapping approach using Sentinel-1 data. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, V-3-2022, 549–556. <https://doi.org/10.5194/isprs-annals>
- [29] Thammaboribal, P., Tripathi, N., Lipiloet, S., & Mandadi, R. (2025). Flood mapping and damage assessment using UN-SPIDER recommended practices in Google Earth Engine: A case study of the 2024 Chiang Rai flood, Thailand. *International Journal of Geoinformatics*, 21(3), 165–179.

- [30] Torres, R., Snoeij, P., Geudtner, D., Bibby, D., Davidson, M., Attema, E., Potin, P., Rommen, B., Floury, N., Brown, M., Traver, I. N., Deghaye, P., Duesmann, B., Rosich, B., Miranda, N., Bruno, C., L'Abbate, M., Croci, R., Pietropaolo, A., ... Rostan, F. (2012). GMES Sentinel-1 mission. *Remote Sensing of Environment*, 120, 9–24. <https://doi.org/10.1016/j.rse.2011.05.028>
- [31] Uddin, K., Matin, M. A., & Meyer, F. J. (2019). Operational flood mapping using multi-temporal Sentinel-1 SAR images: A case study from Bangladesh. *Remote Sensing*, 11(13), Article 1581. <https://doi.org/10.3390/rs11131581>
- [32] Umaru, E., & Adedokun, A. (2020). Geospatial analysis of flood risk and vulnerability assessment along River Benue Basin of Kogi State. *Journal of Geographic Information System*, 12(1). <https://doi.org/10.4236/jgis.2020.121001>
- [33] UN-SPIDER Knowledge Portal. (n.d.). Recommended practice: Flood mapping and damage assessment using Sentinel-1 SAR data in Google Earth Engine. United Nations Office for Outer Space Affairs. Retrieved July 18, 2026, from <https://www.un-spider.org/advisory-support/recommended-practices/recommended-practice-google-earth-engine-flood-mapping>
- [34] Wikipedia. (2026, July 18). Kogi State. In Wikipedia. https://en.wikipedia.org/wiki/Kogi_State
- [35] Zanaga, D., Van De Kerchove, R., Daems, D., De Keersmaecker, W., Brockmann, C., Kirches, G., Wevers, J., Cartus, O., Santoro, M., Fritz, S., Lesiv, M., Herold, M., Tsendbazar, N.-E., Xu, P., Ramoino, F., & Arino, O. (2022). ESA WorldCover 10 m 2021 v200 [Data set]. Zenodo. <https://doi.org/10.5281/zenodo.7254221>