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ADOPTING SENTINEL-1 SAR DATA FOR FLOOD MAPPING: A CASE STUDY OF BORNO STATE, NORTHEASTERN NIGERIA

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Abstract

Flooding is a significant hazard in Nigeria, with factors like climate change, deforestation, and inadequate urban planning increasing the risk. Accurate flood mapping across large areas is crucial for effective disaster management. This study aims to map the flood extent in Borno State triggered by the collapse of the Alou Dam in September 2024 adopting Sentinel-1 Synthetic Aperture Radar (SAR) data from the Google Earth Engine platform. The analysis employed vertical transmit/vertical receive (VV) polarization, which is highly sensitive to vertical structures, making it particularly effective for detecting flood inundation in urban areas. To ensure accurate flood mapping, the SAR data underwent processing, including speckle noise reduction through spatial smoothing using a focal mean filter. Change detection analysis was conducted by comparing SAR images before (July 5–25, 2024) and after (September 5–25, 2024) the flood event. A thresholding technique was applied to differentiate flooded from non-flooded areas, with a threshold of 5 selected after testing various values to minimize false positives, especially in non-flooded rural regions. The results indicated that approximately 356 km² of the 66,224 km² study area was inundated, affecting heavily populated regions such as Jere, Maiduguri, Mobbar, Monguno, Marte, Mafa, and Ngala. The study underscores the need for better urban planning and disaster preparedness in flood-prone areas, with SAR data playing a crucial role in monitoring and mitigating future flood events.

Key Words: *Nigeria, Borno State, Flood, Sentinel-1 SAR, Alou Dam*

Introduction

Flooding is a significant natural hazard often triggered by short-term heavy rainstorms or prolonged precipitation that exceeds drainage capacity (Shahapure *et al*., 2010; Zhang *et al*., 2020). In Nigeria, flooding is influenced by factors such as climate change, deforestation, rapid urbanization, and inadequate infrastructure (Mfon *et al*., 2022; Echendu, 2023). The consequences of floods are severe, causing substantial harm to lives and property (Agbonkhese *et al*., 2014; Abdulrahim *et al*., 2022; Umar and Gray, 2023).

The September 10, 2024, Borno floods, triggered by the collapse of the Alou Dam, affected several regions in Borno State (News Wires, 2024). The flooding submerged key locations, including the Shehu of Borno Palace, the state secretariat, and major markets. In Maiduguri, the Customs area experienced severe flooding. Other impacted areas within Borno included Monguno, Jere, Chibok, Bayo, Hawul, Shani, and Gwoza. According to the press release, continuous rainfall began toward the end of August in the Bama, Damboa, and Gwoza local government areas, causing the water level in the Alou Dam reservoir to rise. On September 10, the dam started to fracture and eventually burst its banks, triggering flash floods that inundated and devastated low-lying communities across the state (Kabir & Abdulkareem, 2024; Isah *et al*., 2024).

While the dam collapse was the cause of extreme rainfall, this study argues that poor urban development exacerbated the severity of the impact. Field observations by Bwala *et al*. (2015) reveal that inadequate drainage systems, blocked channels, improper waste disposal, and unplanned construction over natural drainage paths contribute to recurrent flooding in Borno State. Human activities that degrade the environment further amplify flood risks (Merten *et al*., 2021).

While extreme rainfall was the primary trigger for the dam collapse, this study argues that poor urban development significantly exacerbated the severity of the resulting flood impacts. Field observations by Bwala *et al*. (2015) reveal that inadequate drainage systems, blocked channels, improper waste disposal, and unplanned construction over natural drainage paths contribute to recurrent flooding in Borno State. Additionally, human activities that degrade the environment further amplify flood risks (Merten *et al*., 2021).

As the frequency and intensity of floods increase in Nigeria, there is an urgent need for efficient flood monitoring and mitigation strategies. Understanding the spatial distribution and severity of floods is crucial for disaster prevention (Tavus *et al*., 2019). Accurate flood mapping is essential for disaster preparedness, recovery planning, and improved flood risk management, particularly in vulnerable regions like Borno.

Traditional flood mapping methods, such as ground surveys and optical remote sensing, face challenges like cloud cover, poor weather, and limited accessibility. Ground surveys, although accurate, are time-consuming and resource-intensive, while optical remote sensing systems depend on clear skies, making them ineffective during extreme weather events (Tavus *et al*., 2019). Synthetic Aperture Radar (SAR), particularly Sentinel-1 SAR data, offers a solution. SAR operates in the microwave spectrum, allowing high-resolution imagery capture regardless of weather conditions or cloud cover, making it ideal for flood detection and monitoring (Zhang *et al*., 2014).

SAR has proven to be an economically viable tool for providing first-hand information in flood-affected areas. Recent studies have increasingly adopted Sentinel-1 imagery on cloud-based platforms for flood mapping (Vanama *et al*., 2020; Singha *et al*., 2020; Tiwari *et al*., 2020). Information such as the spatiotemporal location of flooded areas, flood depth, and risk zones is critical for disaster management (Ologunorisa & Abawua, 2005; Panhalkar & Jarag, 2017). SAR systems are effective in all weather conditions and at all times, making them highly suitable for flood mapping (Manavalan, 2017; Vanama *et al*., 2020; Wang *et al*., 2022). Previous studies have shown that SAR systems can generate near real-time flood maps relevant to flood management (Pulvirenti *et al*., 2016; Cohen *et al*., 2019). The main task of SAR-based flood mapping is distinguishing between flooded and non-flooded areas using pixel values (Wang *et al*., 2022).

The availability of Sentinel-1's extensive data archive, along with its high spatial and temporal resolution, makes it well suited for timely flood mapping (Graw *et al*., 2022). Such maps are critical for decision-making during disaster situations (Dumitru *et al*., 2015; Ham and Kim, 2020; Dhanabalan *et al*., 2021).

This study aims to adopt Sentinel-1 SAR data for flood mapping in Borno State, Nigeria, focusing on the September 2024 flood event. By leveraging Sentinel-1's capabilities, this study seeks to identify the areas most severely impacted by floods. The findings will not only contribute to the existing body of knowledge on flood mapping but will also provide practical insights for policymakers and disaster management agencies to mitigate flood risks in Nigeria.

Study area

Borno State, located between latitudes 11°N and 13°N and longitudes 10°E and 14°E, covers an area of 65,868km^2. The State is divided into 27 local government areas (Figure 1). Situated in the northeastern part of the country, it occupies much of the Chad Basin and shares international borders with Niger to the north, Chad to the northeast, and Cameroon to the east (Jimme & Bashir, 2009). Domestically, it is bordered by Adamawa to the south, Yobe to the west, and Gombe to the southwest. According to estimates in 2024, Borno State has a population of approximately 6 million (WANEP, 2024). Borno's landscape transitions from hilly to relatively flat terrain, with elevations ranging from 700 meters above sea level, reaching over 900 meters in the Mandara Mountains, to 228 meters at the shores of Lake Chad in the northeast. The southern part of the state is rugged, with prominent landforms like volcanic mountains, cones, escarpments, craters, and waterfalls on the Biu Plateau, and inselbergs, ridges, and isolated hills on the Mandara Mountains (Jimme and Bashir, 2009). Borno's climate, like much of northern Nigeria, features distinct wet and dry seasons, with rainfall from June to October and dry conditions from November to April. The annual rainfall varies from around 250mm in the north to up to 1,000mm in the Biu Plateau in the south. Flooding is most common during the brief periods of intense rainfall between July and October (Jimme and Bashir, 2009).

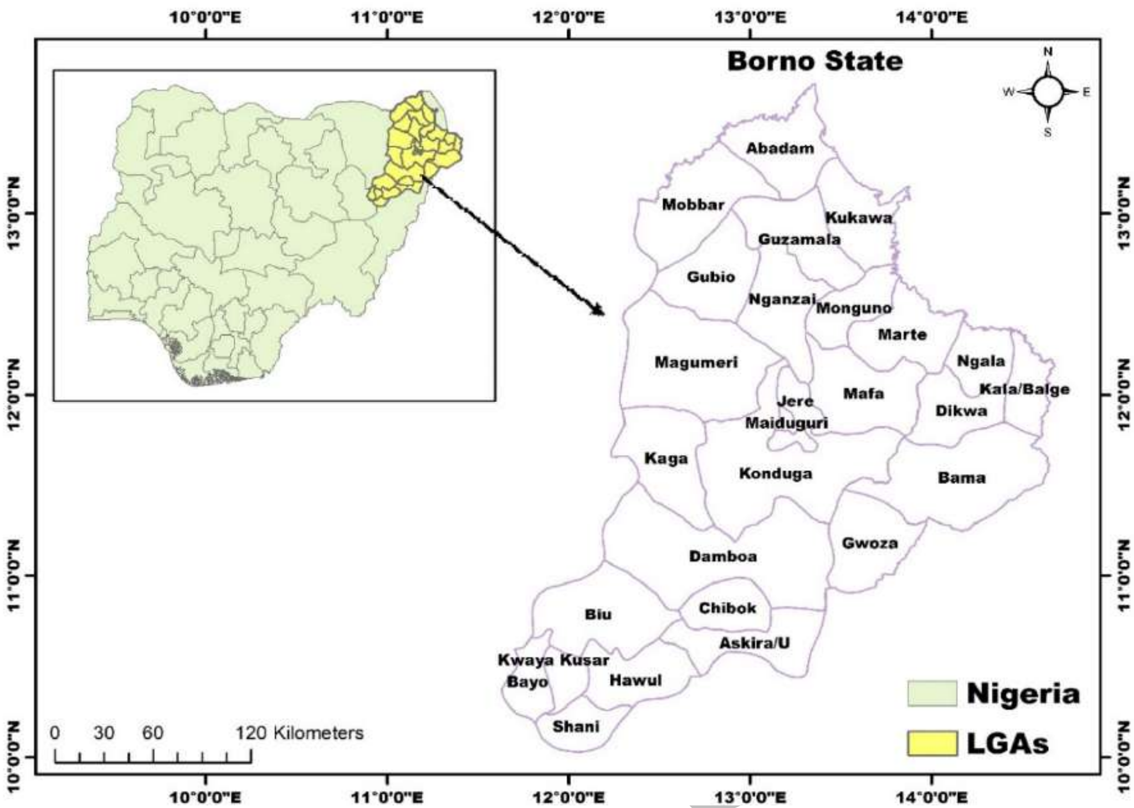

Fig. 1: Map of the study area (Borno State)

Materials and Methods

Datasets and Acquisition

The study utilized Sentinel-1 Synthetic Aperture Radar (SAR) Ground Range Detected (GRD) products, accessed from the "COPERNICUS/S1_GRD" Image Collection on Google Earth Engine (GEE) (Gorelick *et al*., 2017). The datasets include two temporal subsets of SAR data: one before the flood (July 5, 2024, to July 25, 2024) and one after the flood (September 5, 2024, to September 25, 2024).

Sentinel-1 data was selected because radar imaging is independent of weather conditions and daylight, making it highly suitable for disaster management and flood monitoring (Fischell *et al*., 2018; Canty *et al*., 2019). SAR data, with a spatial resolution of 10 meters, was preferred for this study as it is readily available in a pre-processed format that includes thermal-noise removal, radiometric calibration, and terrain correction (Risling *et al*., 2024).

Two key challenges with Sentinel-1 data are its temporal resolution and the potential for "water look-alikes," i.e., objects that reflect similarly to water, such as tarmacs, roads, and wet soil (Shen *et al*., 2019). To mitigate these issues, temporal filtering and thresholding were carefully applied to ensure accurate flood detection. The research methodology is shown in Figure 2. The dataset used for this study is given in Table 1.

Data Preprocessing

The Sentinel-1 SAR data was processed in GEE following the methods outlined by UN-SPIDER (2021). Sentinel-1 SAR data was acquired in the Interferometric Wide (IW) swath mode, which is optimized for land feature acquisition and provides detailed land cover data (Wang *et al*., 2022). VV polarization, which, although less commonly applied in open flood-prone areas compared to VH polarization, was chosen for this study specifically for its higher sensitivity to vertical structures, such as buildings in urban environments. This decision aligns with previous research indicating that VV polarization provides more accurate results in urban settings with significant vertical features (Wang *et al*., 2022).

One of the challenges of SAR data is speckle noise, a granular interference that can obscure critical features (Sebastianelli *et al*., 2022). To address this, the SAR imagery was processed using a focal mean filter with a 60-meter square kernel, utilizing the focal Mean () function in GEE. This filtering technique smooths the imagery by reducing speckle noise while preserving essential details crucial for accurate flood detection. This filter was applied consistently across both the pre-flood (July 5 - July 25, 2024) and post-flood (September 5 - September 25, 2024) images, enhancing signal clarity and ensuring that the flood-detection analysis could effectively differentiate between water and non-water features.

By applying this spatial smoothing technique, the study minimized the risk of false positives, such as "water look-alikes" caused by features like roads or tarmac, further improving the reliability of flood detection (Shen *et al*., 2019). The JavaScript used for this study is shown in Figure 3.

Change Detection

The difference between the pre-flood and post-flood SAR images was calculated using the subtract function in GEE. This process gives a new image that represents changes between the two periods, which can indicate areas impacted by the flood. The change detection image captures pixels with lower negative values where the flood is likely present. To exclude permanent water bodies and focus solely on flood-related changes, a water mask was applied using Dynamic World Image Collection (“GOOGLE/DYNAMICWORLD/V1”) (Brown *et al*., 2022). The water mask was extracted by filtering for the period between 2023 and 2024, isolating the water class from the 'label' band. This mask was then used to filter the change detection results, allowing for the identification of areas where temporary inundation occurred due to flooding.

Thresholding

SAR-based methods for flood detection encompass techniques such as thresholding, image segmentation, statistical active contouring, rule-based classification, and data fusion (Pradhan, 2016). Of these approaches, thresholding is the most widely used due to its efficiency and ability to provide accurate near-real-time flood mapping (Amitrano *et al*., 2018). To identify the areas most severely affected by the flood, a thresholding approach was applied to the change detection map, creating a binary layer that distinguishes between flooded and non-flooded areas (Figure 5). Several thresholds (1.25, 3, and 5) were tested. A threshold of 1.25 is common in flood mapping studies (UN-SPIDER, 2021; Risling *et al*., 2024; Singh & Rawat, 2024), but in this study, both the 1.25 and 3 thresholds resulted in many false positives, particularly in non-flooded rural areas. A false positive refers to instances where an area is incorrectly identified as flooded when it is, in fact, not flooded. After trial and error, a threshold of 5 was selected as it improved accuracy by filtering out most false positives while retaining valid flood-affected regions.

Flood Area Calculation

Once the change detection map was finalized in GEE, the result was exported to ArcGIS 10.7.1 for further analysis. The raster images were reprojected from the WGS 84 coordinate system to UTM Zone 33N. Extract by mask was used to remove the unnecessary background in the raster image. Raster-to-polygon conversion was applied using the ArcGIS tool, and the dissolve tool was used to aggregate contiguous flooded pixels into larger polygons for easier area calculation. The total area of flooded regions was calculated in square kilometres (Table 2).

Table 1: Datasets used for this study

Datasets	Sentinel 1	
Product	SAR GRD	SAR GRD
Acquisition Date	2024-07-05 to 2024-07-25	2024-09-05 to 2024-09-25
Purpose	Pre-flood	Post-flood
Polarization	VV	VV
Beam Mode	IW	IW
Pass	Ascending	Ascending

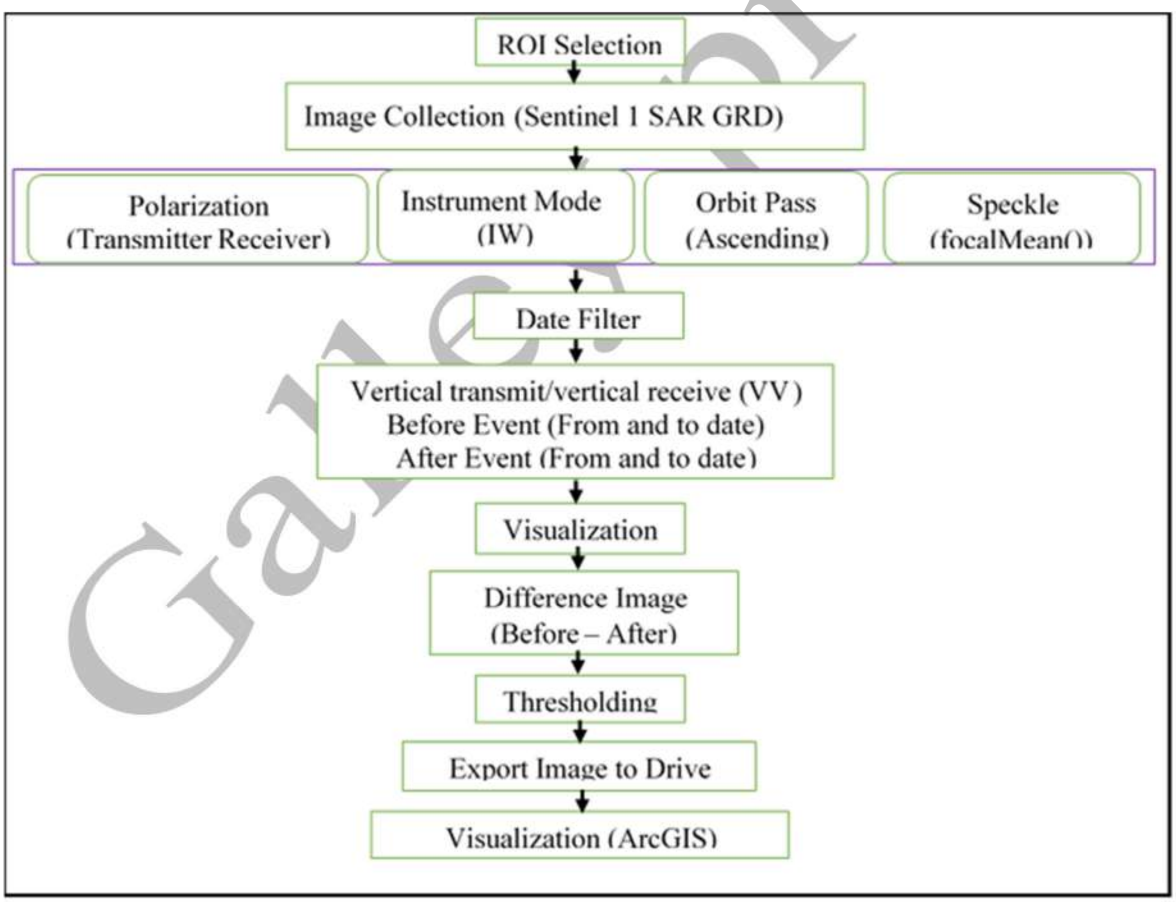

Fig. 2: Research methodology flowchart

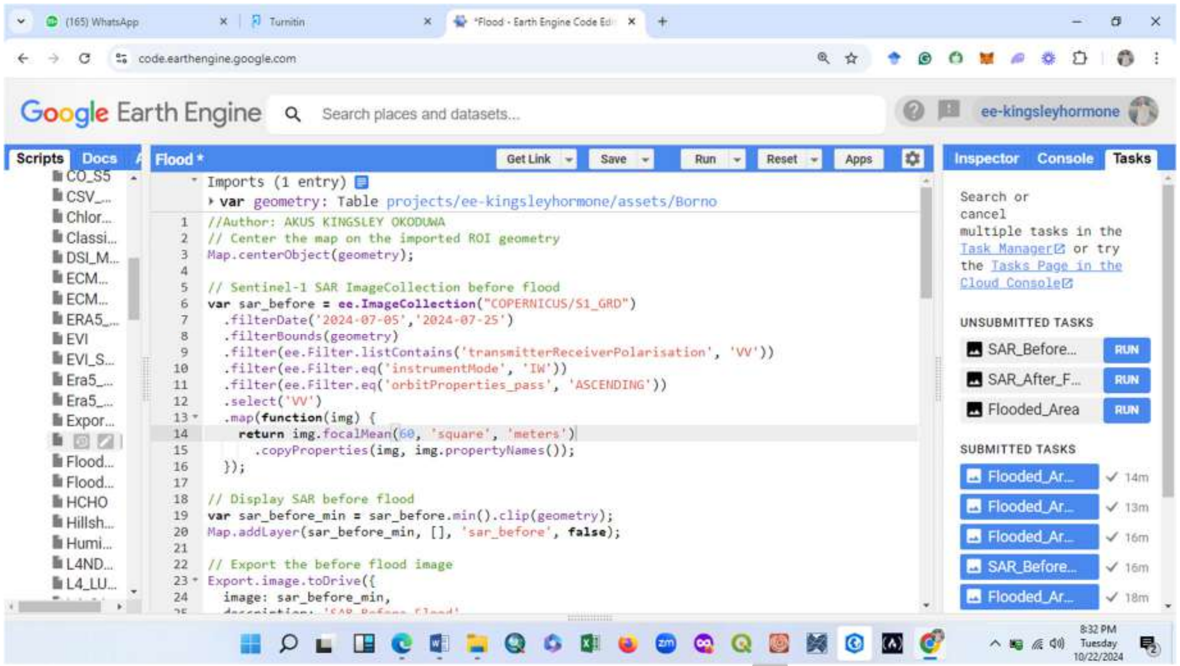

Fig. 3: Code editor window showing JavaScript use for this study

Results and Discussion

Flood Analysis Using Sentinel-1 SAR Data

The flood's extent was analyzed using Sentinel-1 SAR images captured before and after the flood event. The pre-flood image (Figure 4), taken between July 5 - July 25, 2024, serves as a baseline for understanding the changes. The post-flood image (Figure 5), acquired between September 5 - September 25, 2024, provides a snapshot of the flood's aftermath. In the post-flood image (Figure 5), very bright areas indicate changes (presence of water or inundation), while dark areas represent no changes or other land cover types (Ghouri *et al.*, 2024). Through the comparison of pre-and post-flood images, it was possible to identify areas inundated by the flood. This approach helps in understanding how water levels rose and where temporary water bodies or channels were formed due to the flooding.

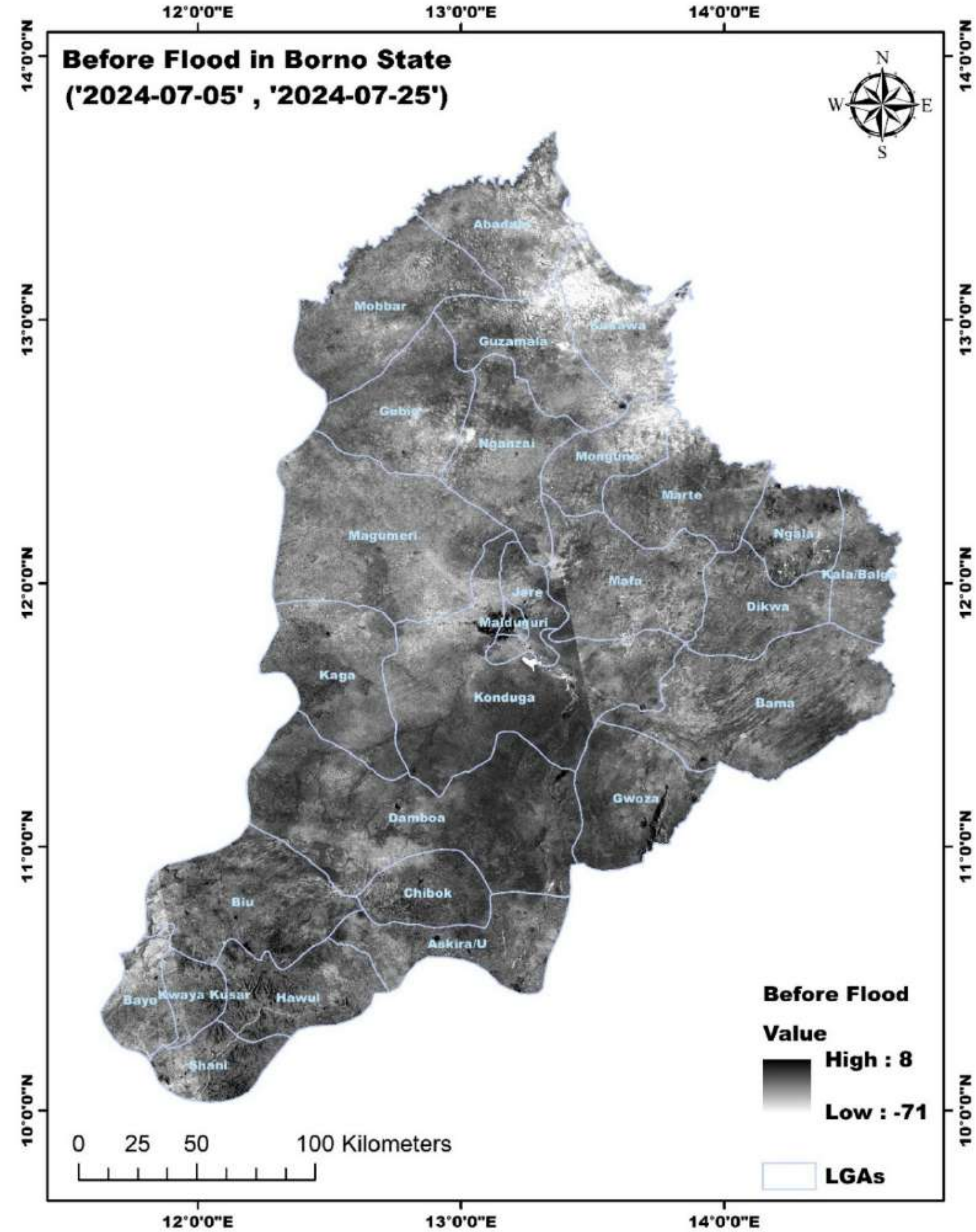

Fig. 4: Image before flooding

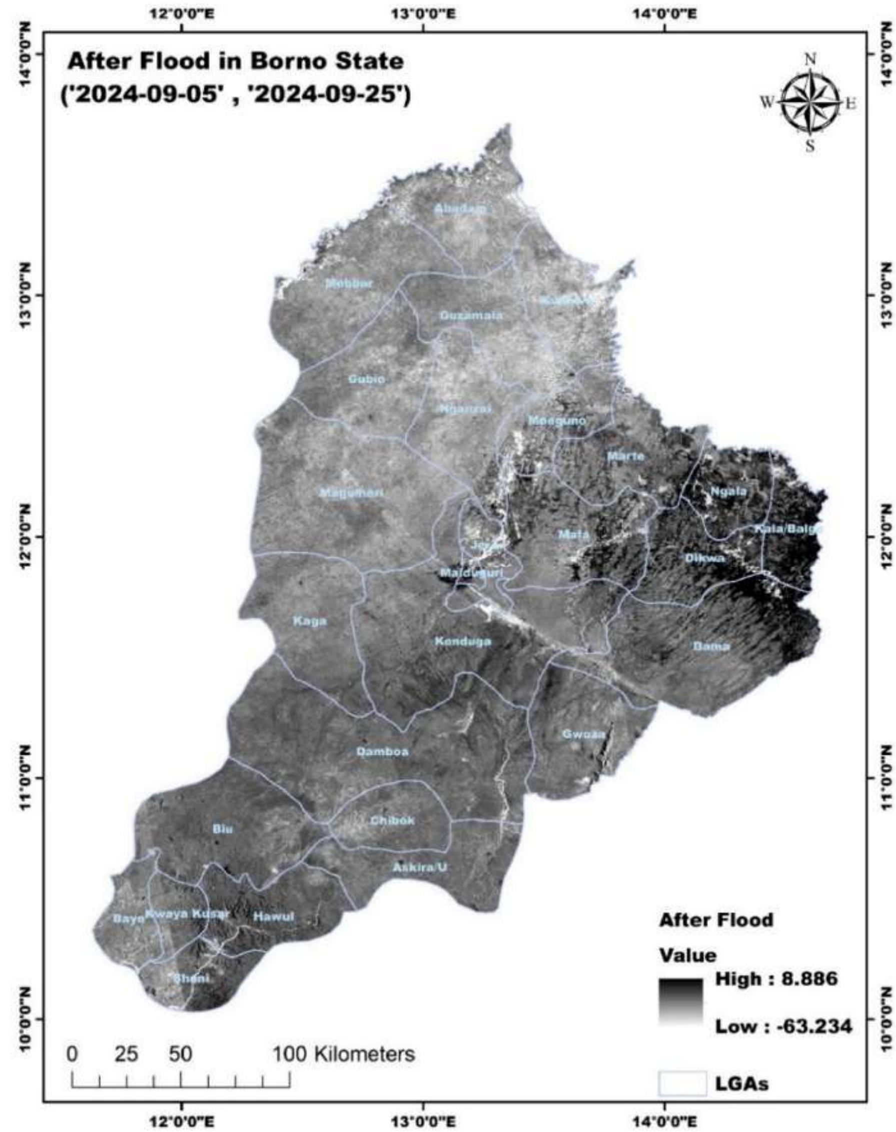

Fig. 5: Image after flooding (very bright areas indicate high change while dark areas indicate no change)

Change Detection Mapping

The change detection map (Figure 6) was created by subtracting the pre-flood image from the post-flood image, resulting in a visual representation of flood-affected areas. This method for flood detection has been used by similar studies (Islam and Meng, 2022; Singh and Rawat, 2024; Ghouri *et al*., 2024). This technique highlights changes caused by the flood and provides insights into the spatial distribution and magnitude of the flood. Such analyses are crucial for supporting authorities in prioritizing recovery efforts and resource allocation for flood mitigation.

According to the change detection analysis, the most severely impacted regions include Jere, Maiduguri, Mobbar, Monguno, Marte, Mafa, and Ngala.

Additionally, flooding patches were observed in areas such as Nganzai, Dikwa, Konduga, Damboa, Gwoza, Chibok, Biu, and Shani.

Flood Area Statistics

The total land area examined in this study covers approximately 66,224 km². The flood affected a total of 356 km², while the remaining 65,868 km² of the area was not inundated, as shown in Table 2.

Table 1: Flood area statistics

Total land area (km^2)	Flooded area (km^2)	None flood area (km^2)
66,224	356	65,868

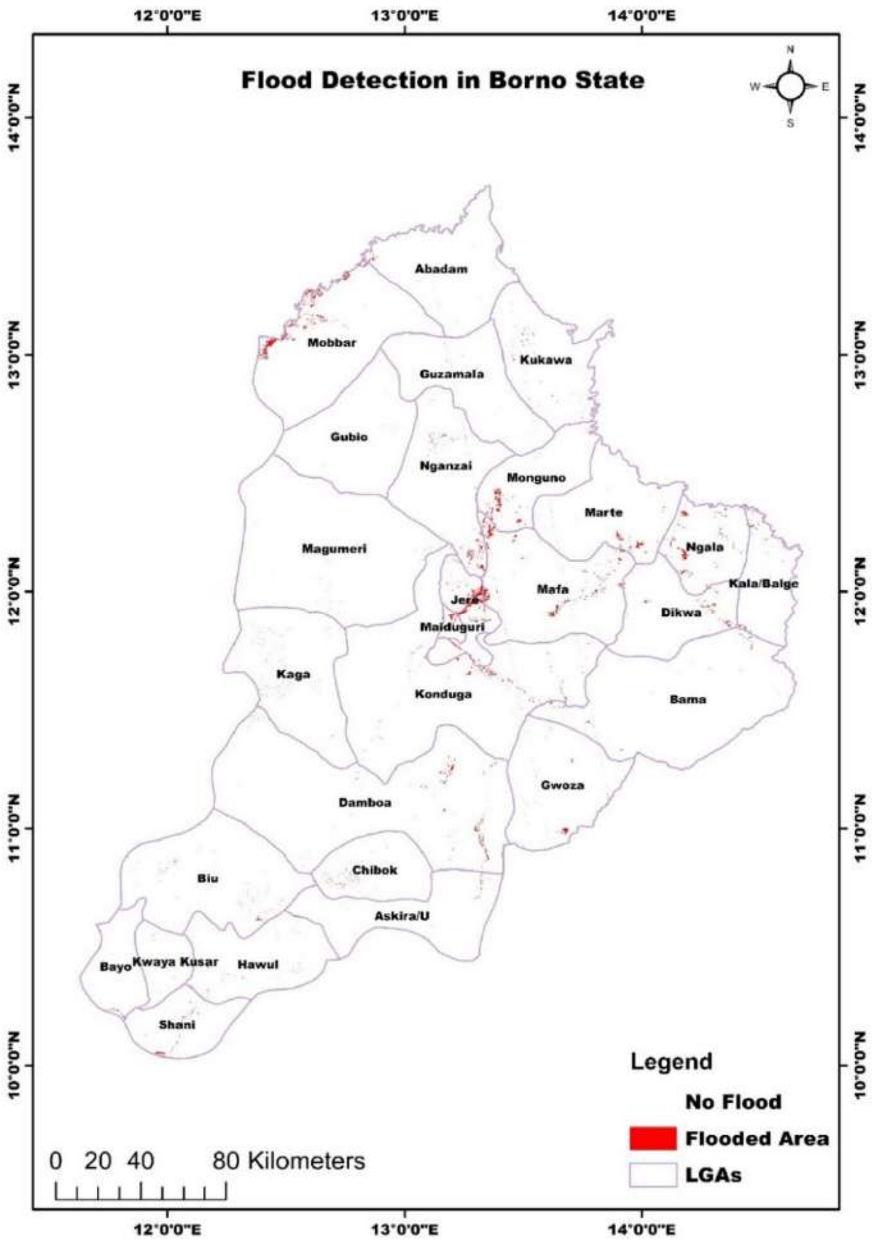

Fig. 6: Flood detection map

The flood affected a relatively small portion of the total land area of Borno State. Out of 66,224km^2, only 356km^2 were flooded, accounting for about 0.54% of the entire study area. While this percentage seems small, the flooded regions included densely populated areas such as Maiduguri and Jere, leading to widespread displacement and loss of life (Kabir & Abdulkareem, 2024; Isah *et al*., 2024). It is important to note that this is not the first time Alau Dam has failed, the dam, originally constructed in 1986 to aid irrigation and control flooding from the Ngadda River, had previously failed in 1994 and 2012, causing significant flooding in local communities (Jimme and Abbas, 2009; Babagana *et al*., 2015; Gutti *et al*., 2024). This is history repeating itself as it was reported that the September 2024 flood displaced thousands of people, damaged infrastructure, and impacted agricultural activities (Kabir and Abdulkareem, 2024; Isah *et al*., 2024).

From the result of this study, Maiduguri and Jere local government regions are the hardest-hit areas. According to the reports of Kabir and Abdulkareem. (2024) and Isah *et al*. (2024), the flood claimed the lives of at least 38 people and displaced over 70% of Maiduguri's residents. Additionally, the Sanda Kyarimi Park Zoo, a key wildlife location in Maiduguri, experienced the death of 40% of its animals, while others escaped and were seen roaming the streets of the capital (Mansur and Yusuf, 2024; The Guardian, 2024).

Limitation of Studies and Future Direction

The study relied on satellite data and did not incorporate field validation to corroborate the flood extent findings. This lack of ground truth data could limit the accuracy of flood area delineation. Future research should Incorporate ground-based flood measurements and community reports which can enhance the accuracy of satellite-based flood mapping.

Conclusion and Recommendation

The 2024 Borno floods, triggered by the collapse of the Alou Dam, highlight the vulnerability of flood-prone regions in Nigeria. This study demonstrates the effectiveness of Sentinel-1 SAR data in mapping flood extents. The spatial analysis revealed that although the flooded area covered only 0.54% of the total landmass, its impact on heavily populated areas, such as Maiduguri and Jere, was devastating. To mitigate flooding in Borno State, there is a need to improve drainage systems in urban areas. Constructing effective stormwater management systems will help reduce flooding in the most severely affected areas. If the existing drainage systems are too small to handle large volumes of runoff, they need to be expanded to manage excess water. In addition, deforestation must be curbed, and sustainable land use practices should be promoted. Reforestation efforts to increase tree cover in flood-prone areas can reduce surface runoff and enhance water retention. Awareness campaigns that educate communities about flood risks and encourage them to adopt precautionary measures should also be implemented. Above all, flood risk management should be integrated into national development planning, as this is essential for ensuring a sustainable, long-term approach to managing flood risks.

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ENHANCEMENT OF GERMINATION POTENTIALS OF AFRICAN OIL BEAN (*Pentaclethra macrophylla*) USING DIFFERENT PRE-TREATMENT TECHNIQUES

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Abstract

An experiment was conducted on enhancement of germination of Pentaclethra macrophylla seed at Forestry Research Institute of Nigeria. Seeds were subjected to three different mechanical scarification treatments, three water treatments and a control to break the seed dormancy. The experiment was a complete randomized design replicated three times. Seedling emergence was observed daily. Number of days to first seedling emergence, interval between first and last emergence, duration of emergence, germination count and percentage germination were assessed. Germination indices: SG, MGT, MDG, PV and GV were calculated using the method of Czabator (1962). Mean germination count was also analyzed using analysis of variance (ANOVA) and separated with Duncan Multiple Range Test at 5% level of probability. From the result, T1 (73.33%) and T2 (60%) performed better than other treatments and control (20%). Days to seedling emergence and interval between germination were considerably lower at T1 (8; 9) and T2 (7; 9) compared to other treatments including control (19; 18). The SG was lowest at T4 and control (0.09, 0.12) while the PV and GV were highest at T1 (0.33, 0.215) andT2 (0.29, 0.168) respectively, the least value of PV and GV (0.05, 0.004) were observed on control. The result from mean separation showed that T1 (3.67) and T2 (3.00) were significantly higher compared to control and better than other treatments. To enhance the improvement of the species, seeds of Pentaclethra macrophylla should be mechanically scarified preferably at the hilum point as this will prompt germination and facilitate uniformity in seedlings growth.

Key Words: *Indigenous Species, Pentaclethra. macrophylla, Pre-treatment, Plant improvement, Seed dormancy*

Introduction

Most of the time research attention focuses on some well-known species neglecting some indigenous but useful one. Among these natives species is *Pentaclethra macrophylla* Benth, it commonly known as African oil bean or Congo acacia. The African oil bean (*Pentaclethra macrophylla* Benth) is a tropical tree crop found mostly in the Southern and Middle Belt Regions of Nigeria and in other coastal parts of West and Central Africa. It belongs to the Leguminosae family and the sub-family of Mimosoideae with no known varietal characterization (Keay, 1989, Asoegwu *et al*., 2006). The Yoruba call it Apara or pala while the Igbo called it Ugba