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Geospatial Modelling and Remote Sensing Assessment of Flood-Induced Land Degradation in Nigeria's Middle Belt

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Abstract

Flooding is a natural hydrological phenomenon, caused by natural and human-induced factors, that occurs when water temporarily inundates land that is normally dry. The direct impact of this could include the loss of human lives, displacement of populations, destruction of homes, roads, bridges, farmlands, and public utilities, and damage to economic assets. Meanwhile, the indirect effect could include disruption of livelihoods, food insecurity due to crop loss, degradation of soil quality, and long-term socio-economic setbacks. This study employed geospatial techniques, including remote sensing, field survey, and GIS-based Multi-Criteria Decision Analysis (MCDA), to assess flood-induced land degradation in the Middle Belt of Nigeria. The methodology involved analysing Landsat 9 imagery for land use/land cover (LULC) classification, computing the Normalized Difference Water Index (NDWI) for water body detection, and using Shuttle Radar Topography Mission (SRTM) data for terrain analysis. Field-collected GPS coordinates of historically flooded areas were overlaid for validation. LULC Classification revealed that vegetation dominated the landscape (72.64%), followed by bare land (11.6%), forest (11.37%), built-up areas (3.75%), and water bodies (0.64%). Built-up areas, though minimal in coverage, were categorized as high risk due to impermeable surfaces, which accelerate runoff. Through the MCDA weighted overlay, the final flood risk model classified the region into Low (0.3%), Medium (84.8%), and High (13.8%) flood risk zones. High-risk areas were largely associated with built-up, low-lying, and river-adjacent areas. The integration of remote sensing, terrain data, and field surveys provided a scientifically validated model for flood risk and land degradation mapping in the Middle Belt area of Nigeria, therefore it is recommended for use.

Keywords: Flood, Land Use/Land Cover, NDWI, MCDA, SRTM, Water Bodies.

Introduction

Nigeria's Middle Belt region, comprising states such as Benue, Plateau, Nasarawa, Taraba, and parts of Niger and Kaduna states, represents one of the most flood-prone areas in West Africa (Adeloye & Rustum, 2011; Ityonzughul, 2024). This region, characterized by its transitional position between the northern savanna and southern forest zones, experiences intense seasonal flooding that has become increasingly frequent and severe over the past decades (Nkeki et al., 2013; Badamosi et al., 2024; Ekebuike et al., 2024). The combination of topographic features, including the confluence of major rivers such as the Benue and Niger, coupled with changing precipitation patterns due to climate variability, has made the Middle Belt particularly vulnerable to flood-induced environmental degradation (Okonofua & Kayode-Ojo, 2023).

Flooding in the Middle Belt has evolved from a periodic natural phenomenon to a persistent environmental challenge that significantly contributes to land degradation processes (Huang et al, 2018). The region's agricultural landscape, which supports over 70% of Nigeria's food production, faces increasing threats from flood-related soil erosion, nutrient depletion, and habitat destruction (Ologunorisa & Tersoo, 2006). These flood events not only remove fertile topsoil but also alter the physical and chemical properties of agricultural lands, leading to reduced productivity and long-term ecological damage (Njoku & Efiong., 2020).

Traditional methods of flood assessment and land degradation monitoring in Nigeria have relied heavily on ground-based observations and conventional surveying techniques, which are often inadequate for capturing the spatial and temporal dynamics of flood-induced environmental changes (Nwilo et al., 2012; Akintola, 2024; Ogbole et al., 2025). The limitations of these approaches include their time-consuming nature, high costs, limited spatial coverage, and inability to provide real-time monitoring capabilities (Ideki & Weli, 2019). These constraints have created significant gaps in understanding the comprehensive impacts of flooding on land degradation processes across the Middle Belt region.

The advent of remote sensing technology and geospatial modeling has revolutionized environmental monitoring and assessment capabilities, offering unprecedented opportunities for comprehensive flood impact analysis (Tehrany et al., 2013). Satellite-based remote sensing platforms, including Landsat imagery, provide multi-temporal and multi-spectral data that enable the detection, mapping, and monitoring of flood events and their environmental consequences across large geographical areas (Huang et al., 2018). These technologies facilitate the development of sophisticated geospatial models that can integrate various environmental parameters to assess flood-induced land degradation patterns with high spatial and temporal resolution.

The socio-economic impacts of flood-induced land degradation extend beyond agricultural losses to include displacement of rural populations, destruction of infrastructure, loss of biodiversity, and increased poverty levels (Eguaroje et al., 2015; Ogunribido & Ogunribido, 2024; Echendu, 2020). The degradation of agricultural lands forces farmers to abandon their traditional farming areas, leading to rural-urban migration and increased pressure on urban resources (Nyong et al., 2007). Additionally, the loss of vegetation cover and soil fertility contributes to desertification processes, further exacerbating environmental degradation and reducing the region's capacity to support sustainable livelihoods (An et al., 2019; Chaudhuri et al., 2023).

Despite the severity of these challenges, there exists a significant gap in comprehensive spatial flood modeling and assessment of land degradation impacts in the Middle Belt region. Current understanding of flood-induced land degradation patterns remains fragmented and localized, lacking the spatial resolution and temporal coverage necessary for effective environmental management and policy formulation (Nkan & Umoh, 2016). The absence of integrated geospatial models that can capture the complex interactions between flood events and land degradation processes has hindered the development of effective mitigation strategies and adaptive management approaches.

Traditional monitoring methods employed in the region have proven inadequate for addressing the scale and complexity of flood-induced land degradation challenges (Nwilo et al., 2012). Ground-based surveys, while providing detailed local information, are limited in their spatial coverage and temporal frequency, making it difficult to capture the dynamic nature of flood events and their environmental consequences (Ideki & Weli, 2019). These methods are also costly and time-consuming, constraining their application for large-scale monitoring and assessment activities.

The lack of reliable and up-to-date spatial information on flood-induced land degradation has created significant challenges for environmental managers, urban planners, and policy makers in developing effective response strategies (Okonofua & Kayode-Ojo, 2023; Echendu, 2020; Purity & Eze, 2023). Without accurate and comprehensive data on the spatial distribution and severity of land degradation impacts, it becomes difficult to prioritize intervention areas, allocate resources effectively, and implement targeted restoration and conservation measures (Pham et al., 2016; Adelekan et al., 2015; Ogbole et al., 2025).

Furthermore, the limited integration of remote sensing data with field-based observations has resulted in models and assessments that may not adequately reflect ground-truth conditions (Huang et al., 2018; Mubonderi et al., 2025; Zhang et al., 2023). This disconnects between remote sensing capabilities and field validation has reduced the reliability and applicability of existing flood assessment studies in the region, limiting their utility for practical decision-making and policy development. This study aims to develop a comprehensive geospatial model for assessing flood-induced land degradation in Nigeria's Middle Belt region through the integration of remote sensing data and field survey observations to support evidence-based environmental management and disaster risk reduction strategies.

This study focuses on the confluence area in the Middle Belt region of Nigeria, encompassing the states of Benue, Plateau, Nasarawa, Taraba, and parts of Niger and Kaduna states (Nnaeto, 2025; Nwankwo, 2024). The study area covers approximately 297,314 square kilometers and represents the transitional zone between Nigeria's northern savanna and southern forest regions. The selection of this area is based on its high vulnerability to flood events, significant agricultural importance, and the availability of adequate remote sensing data coverage. The objective of this study is to assess the flood-induced land degradation in the study area using a combined multi-criteria remote sensing and GIS approach.

MATERIALS AND METHODS

The coordinates of flood-prone areas and historical flood points within the study area were collected using handheld GPS devices. The Landsat 9 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) imagery was obtained from the USGS Earth Explorer platform, covering Path/Row 191/055, which includes the Middle Belt area. This satellite imagery has a spatial resolution of 30 meters and was used to analyze land use/land cover (LULC) changes, water body expansion, and vegetation loss, which are critical for identifying flood-prone zones. The raster dataset facilitated classification and change detection analysis, forming the basis for evaluating flood risks.

Data for rivers, was accessed via google Earth Plugin in ArcMap to support the spatial framework of the study. The vector data (lines) were used for proximity analysis to assess flood risks near infrastructure and settlements. Digital Elevation Models (DEMs) derived from the Shuttle Radar Topography Mission (SRTM) were obtained through the USGS Earth Explorer with a spatial resolution of 30 meters. The DEM was used to analyze topographic features such as elevation and slope, which are critical for identifying low-lying and flood-prone areas.

Historical rainfall data from NiMet was used to correlate precipitation patterns with flood occurrences. This data helped in understanding the temporal aspects of flooding in the study area. Table 1 shows Data Sources and metadata used in this study.

Table 1: Data Sources and Descriptions.

Data Type	Data	Source	Spatial Resolution	Temporal Coverage	Format
Landsat 9 OLI/TIRS	LULC NDWI	USGS Earth Explorer	30 m	Jan 2025 (dry)	Raster (GeoTIFF)
SRTM DEM	Slope Elevation	NASA/USGS Earth Explorer	30 m	2020	Raster (GeoTIFF)
RIVERS		Google Earth Plugin in ArcMap	vector data	2024	Vector (Shapefile)
Rainfall Data	Rainfall	Nigerian Meteorological Agency (NiMet)	Point data	2025	CSV / Excel

Data Processing

Geometric correction was carried out to ensure the satellite image accurately reflected the real-world location of surface features. This correction involved aligning the image to a standard coordinate system, UTM Zone 31N with the WGS 84 datum, to eliminate distortions resulting from Earth's curvature, terrain variation, and sensor perspective. Radiometric correction was applied to normalize the spectral reflectance values of the Landsat imagery. This step removed atmospheric and sensor-related distortions that can affect pixel brightness values. Adjustments were made for solar angle, path radiance, and sensor noise to ensure consistency across spectral bands. The correction was necessary to accurately compute indices such as the NDWI and perform supervised classification. Surface reflectance products were generated using top-of-atmosphere (TOA) correction methods, applying gain and bias coefficients provided in the metadata.

Land Use and Land Cover (LULC) Classification

The classification of land cover was performed using the Supervised Classification method, specifically the Maximum Likelihood Algorithm (MLA), within ArcGIS Pro. This method was chosen due to its robustness in handling diverse land features by evaluating statistical probability distributions. Training samples were created by digitizing polygons that represent known land cover types within the study area. These samples were derived from a combination of high-resolution base maps, field observations using GPS coordinates, and visual interpretation of the Landsat image. For each land cover type, multiple training sites were selected to capture spectral variability within that class, ensuring that the classifier can generalize well across the entire image.

Once the training data were prepared, the classification was executed using the Maximum Likelihood algorithm. The classifier analyzed the spectral characteristics of each pixel and compared them against the training samples to determine the most likely class membership.

Water Body Detection Using NDWI

The Normalized Difference Water Index (NDWI) is a widely used remote sensing technique for detecting open water features. It enhances the presence of water while suppressing noise from vegetation and urban surfaces. The NDWI was calculated using the standard equation:

$$NDWI = (Green - NIR) / (Green + NIR) \quad \text{Equation 1}$$

In this study, Band 3 (Green: 0.53–0.59 μm) and Band 5 (Near-Infrared: 0.85–0.88 μm) from the Landsat 9 OLI sensor were utilized. The result of this computation yields a raster with values ranging from -1 to +1. Positive values typically indicate water bodies, while negative values suggest vegetation or urban areas. Thresholds were set empirically by examining histogram values and validating with river and lagoon features visible in high-resolution base maps to isolate strong water signals. This process produced a binary water map showing the spatial extent of water during the time of acquisition.

Terrain Analysis Using Digital Elevation Model (DEM)

Using ArcGIS Pro's Spatial Analyst tools, slope and elevation maps were derived from the DEM. The elevation map classified areas into three categories: low (<10 meters), moderate (10–20 meters), and high (>20 meters), with the low-lying zones marked as highly vulnerable to flood events. The slope map was generated to measure terrain steepness and was grouped into 0–2%, 2–5%, and >5% classes. Flat terrains (0–2%) were identified as water retention zones that contribute to surface flooding. The elevation and slope datasets were reclassified, standardized, and later weighted for integration into the Multi-Criteria Evaluation (MCE). These topographic layers helped spatially delineate where water is likely to accumulate during heavy rainfall events. By integrating the elevation and slope data into the flood modeling process, it was possible to assess the relative flood risk of various terrain types. These terrain indicators are essential for land-use planning, urban drainage design, and identifying areas where construction may require flood-resistant infrastructure.

Integration with GIS and Validation

All processed raster and vector datasets, including the LULC map, NDWI water index, elevation, and slope models, were integrated within a unified GIS environment in ArcGIS Pro. Each layer was standardized to the same spatial resolution (30 meters) and coordinate reference system (WGS 84, UTM Zone 31N) to ensure proper alignment and compatibility. Raster data were converted to integer formats and reclassified on a uniform scale (1 to 3) for risk analysis. These layers were then organized into a geodatabase and served as the geospatial foundation for the flood risk modeling. This integration ensured seamless overlay and spatial computation during the Multi-Criteria Decision Analysis (MCDA).

To validate the accuracy of remote sensing outputs, GPS-based field data were collected from historically flooded areas within Middle Belt. These point datasets were overlaid on the NDWI map, classified LULC image, and DEM-derived flood risk indicators. Areas where remote sensing predictions overlapped with known flood zones provided empirical evidence of model accuracy.

Multi-Criteria Decision Analysis (MCDA)

The Multi-Criteria Decision Analysis (MCDA) approach was applied to evaluate flood susceptibility in the study area by integrating several geospatial variables that influence flood occurrences. These variables were selected based on field observations, expert knowledge, and literature reviews. Five geospatial criteria were selected for inclusion in the flood risk model: elevation, slope, proximity to water bodies, land use/land cover, and rainfall intensity. These factors are commonly associated with hydrological response and flood generation. Elevation and slope influence the direction and speed of water flow, while land use determines surface permeability. Proximity to rivers and lagoons increases the likelihood of direct flooding. Rainfall intensity directly correlates with the volume of runoff generated. Each of these criteria was represented as a raster layer and subjected to classification into three flood risk levels—low, moderate, and high.

Weights were assigned to each standardized criterion to reflect its relative influence on flood susceptibility. Elevation was given the highest weight of 25% due to its strong correlation with water accumulation in low-lying areas. Slope and proximity to water bodies were each assigned 20%, recognizing their role in surface runoff and direct exposure to flood sources. Rainfall intensity also received 20%, acknowledging its impact on flood volume and frequency. Land use was assigned 15%, reflecting human-related vulnerability.

Classification Accuracy Assessment

The supervised Maximum Likelihood Classification (MLC) was validated using GPS-based field points and reference imagery. GPS coordinates of historically flooded locations collected within the Middle Belt region were overlaid on: NDWI raster map, reclassified LULC map, elevation/slope layers and final MCDA flood risk map. Spatial coincidence between known flood points and predicted high-risk zones was used as a primary validation indicator.

RESULTS AND DISCUSSION

Land Use and Land Cover Classification Analysis

The spatial distribution of land use and land cover classes within the study area is illustrated in Figure 1 and statistically summarized in Table 2. The analysis shows that vegetation is the most dominant class, covering approximately 72.64% (6,391,052 ha) of the total area. This is followed by bare-land (11.6%), forest (11.37%), built-up areas (3.75%), and water bodies (0.64%).

Table 2: Land use and Land Cover

S/N	NAME	AREA	PERCENT
1	Waterbody	56706.12	0.64
2	Bare-land	1021017	11.6
3	Built-up	329710.3	3.75
4	Vegetation	6391052	72.64
5	Forest	1000244	11.37

Despite their small areal extent, built-up areas are critically important in flood studies due to the impervious nature of urban surfaces which inhibit infiltration and increase surface runoff. The dominance of vegetative cover suggests that the landscape is largely natural, which could enhance infiltration.

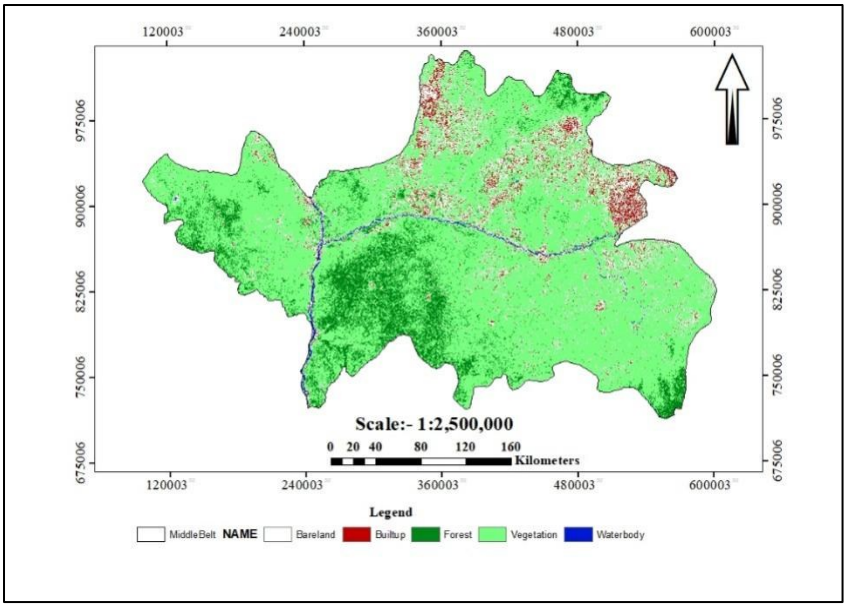


Figure 1: Land use and Land Cover Map

Elevation Analysis

The elevation map (Figure 2) reveals a varied topographic landscape, with lower elevations concentrated in specific regions. Areas below 10 meters above sea level are particularly prone to flood accumulation due to gravitational water flow and poor natural drainage. These low-lying regions often act as floodplains, accumulating runoff from adjacent higher grounds.

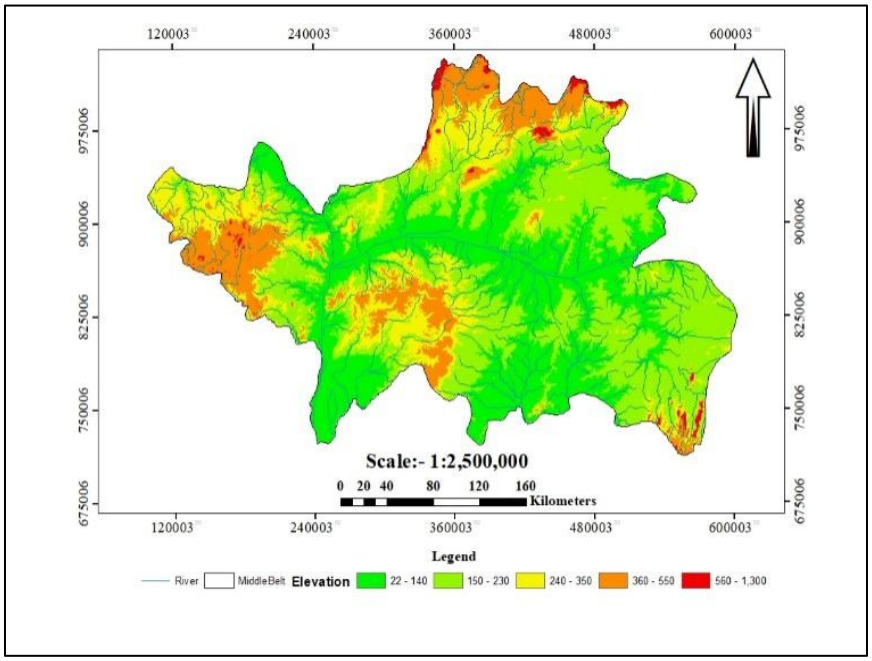


Figure 2: Elevation Analysis

Multi-Criteria Decision Analysis (MCDA)

The integration of multiple flood-influencing parameters was conducted using MCDA, which combines environmental variables based on assigned weights and scores. The criteria and their corresponding weights are summarized in Table 3.

Table 3: Summary Table for Criteria Decision Analysis.

Criterion	Description	Class	Score	Weight
Elevation	<10m = High Risk	High	3	25%
Slope	0–2% = High Risk	High	3	20%
Proximity to Water	<1000m = High Risk	High	3	20%
LULC	Built-up = High Risk	High	3	15%
Rainfall	>273mm/month = High Risk	High	3	20%

The LULC classes were reclassified based on their potential to influence flood behavior. As shown in Figure 3, built-up areas, though occupying only 3.75% of the land, were designated as high risk due to their impervious surfaces that accelerate surface runoff and prevent water infiltration. Vegetation and forested lands were categorized as medium risk because they offer moderate resistance to flooding by enhancing infiltration and reducing runoff velocity. Water bodies, which are inherently flood-holding zones, were classified as low risk.

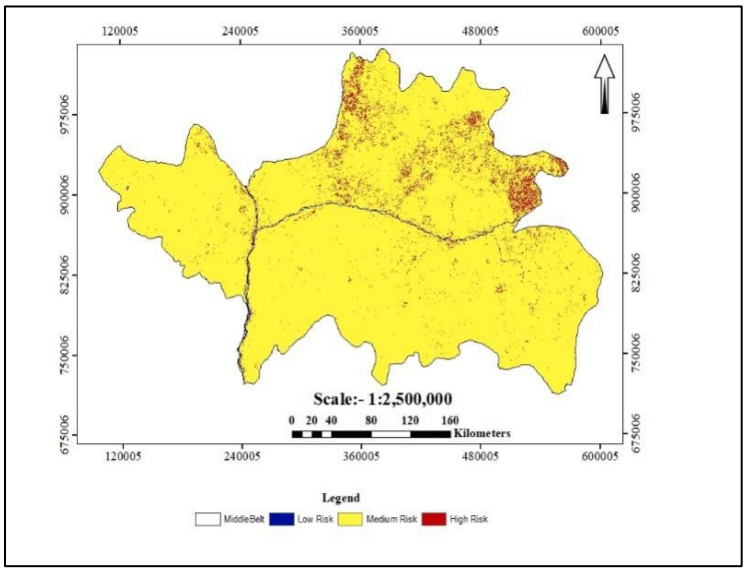


Figure 3: Reclassification Analysis of LULC

Elevation plays a crucial role in flood accumulation and drainage. In this study, areas below 10 meters above sea level were assigned to the high-risk category due to their natural tendency to collect runoff as shown in figure 4. These low-lying regions lack the gravitational advantage to channel water away effectively, making them susceptible to waterlogging. Mid-elevation areas were designated as medium risk, while elevated terrains were considered low risk.

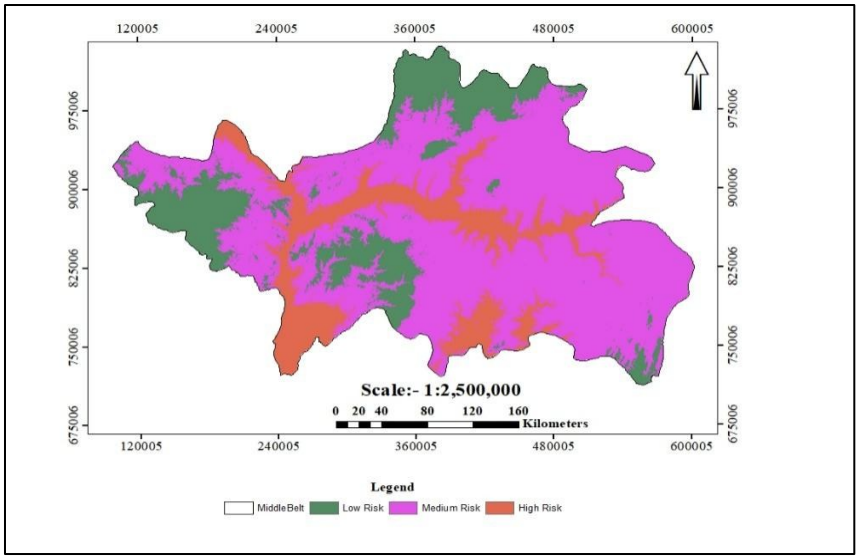


Figure 4: Reclassification Analysis of Elevation

In figure 5, areas with slopes between 0–2% were categorized as high risk, since flat terrains encourage water pooling and slow drainage. Moderate slopes (2–5%) fell under the medium-risk category, while steeper slopes (>5%) were considered low risk, as they facilitate quick runoff and less stagnation.

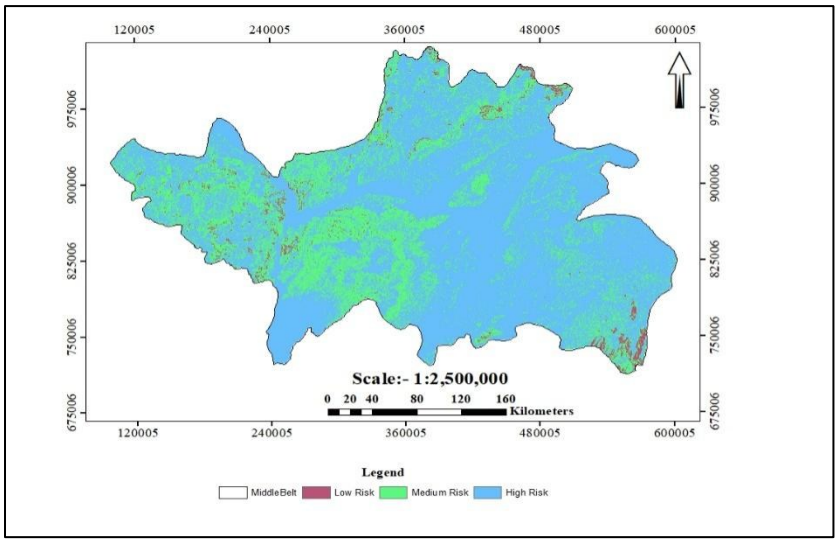


Figure 5: Reclassification Analysis of Slope

Rainfall is a primary trigger of flooding. In this study (see figure 6), areas receiving more than 273 mm/month were classified as high risk, as this threshold represents a critical point for excessive surface runoff generation. Zones receiving between 150–273 mm/month were deemed medium risk, while lower rainfall areas were classified as low risk.

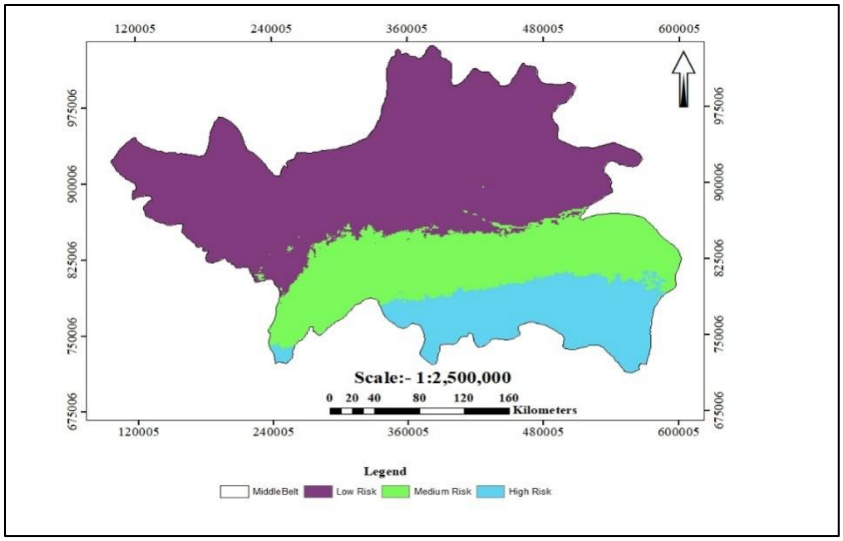


Figure 6: Reclassification Analysis of Rainfall Distribution

Proximity to river systems is a major flood vulnerability indicator, especially in floodplain regions. In this analysis (see figure 7), areas within 1000 meters of a river channel were classified as high risk due to their immediate exposure to river overflow and catchment runoff. Zones between 1000–3000 meters were considered medium risk, and those beyond 3000 meters were marked low risk.

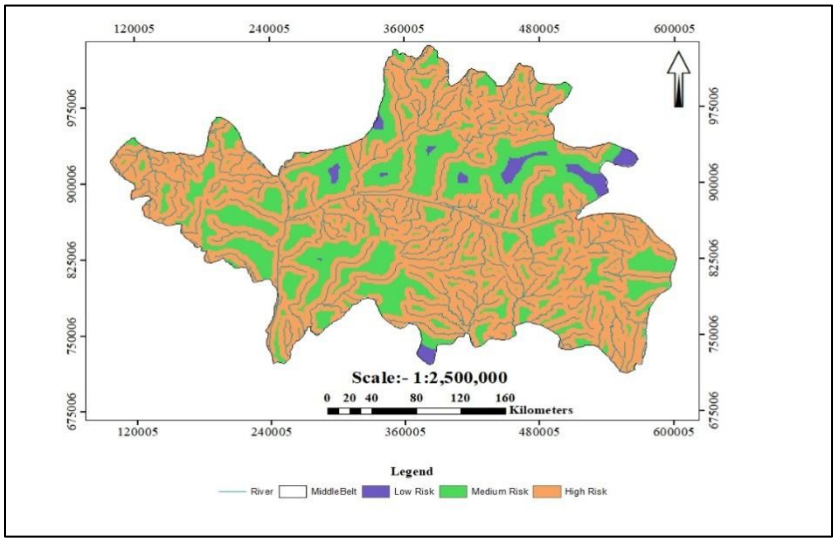


Figure 7: Reclassification Analysis of River Network

Normalized Difference Water Index (NDWI)

The NDWI was applied to assess the spatial moisture content of the land, using remotely sensed spectral indices. This index is vital for detecting water saturation levels in soils and identifying areas likely to become inundated during rainfall events. NDWI is especially useful

in supplementing physical flood variables like slope and proximity to water bodies by offering a dynamic view of the moisture condition of the surface.

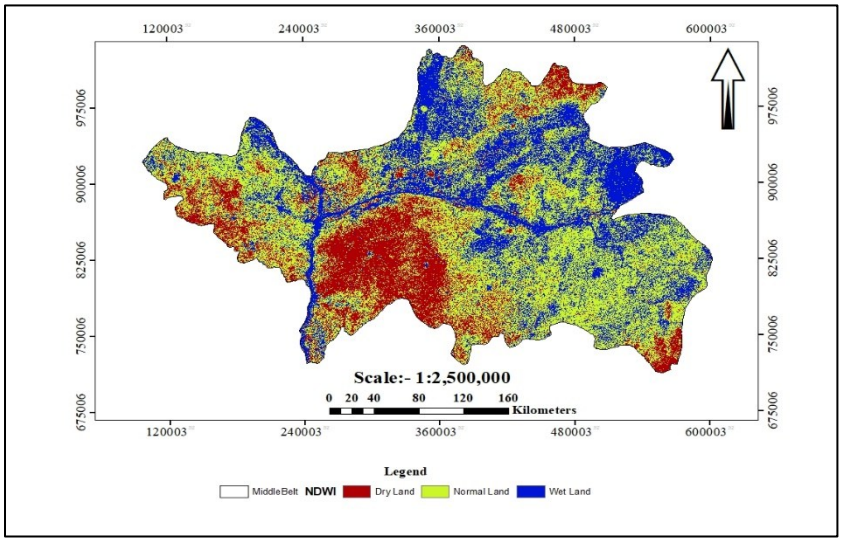


Figure 8: Normalize Difference Water Index of the Study Area

Figure 8 presents the NDWI map and the NDWI results were categorized into three classes: Dry Land, Normal Land, and Wet Land. These classes reflect varying degrees of surface moisture, which directly influence infiltration and runoff dynamics. Figure 9 shows the proportion of each class in chart form. Nearly one-third of the landscape is classified as Wet Land, highlighting significant areas at risk of surface saturation. These regions are most likely to become waterlogged during rainy seasons, especially when overlaid with low elevation and low slope zones.

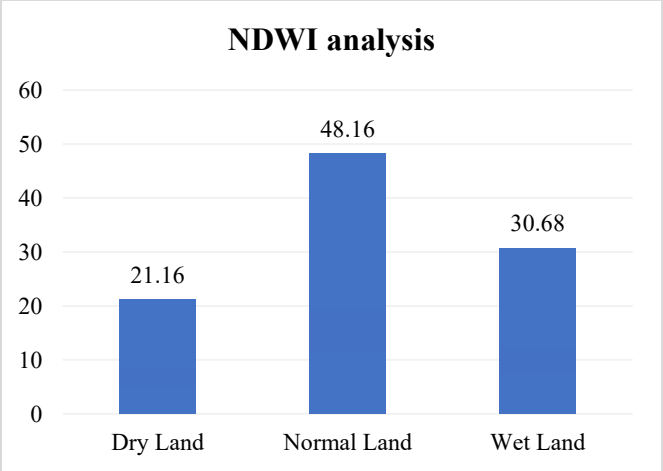


Figure 9: NDWI Analysis Chart

The NDWI findings align with the reclassified flood risk factors, adding depth and spectral validation to the spatial analysis. The Normal Land class dominates the landscape, suggesting that while parts of the region have balanced moisture conditions, a large portion still retains enough water to pose moderate flood threats. The Dry Land category, though least extensive, corresponds with elevated, well-drained terrains.

Flood Induced Map Model

The final output of the flood modeling is shown in the Flood Risk Map (Figure 10). This map provides a detailed spatial representation of flood-prone zones, serving as a crucial tool for planners, disaster managers, and policy makers.

From the table, it is evident that the Medium Risk class constitutes the majority of the study area, encompassing approximately 84.8% of the total land. This zone includes regions with moderate slope, elevation, rainfall, or vegetation cover, where flooding is likely under extreme weather conditions or due to poor drainage. The High-Risk class, which comprises about 13.8%, is largely concentrated in built-up, flat, and low-lying locations near river courses. These areas are of immediate concern for flood mitigation measures.

Conversely, Low Risk zones account for only 0.3% of the total area, typically found in elevated, well-drained, and low-rainfall regions. These areas are ideal for critical infrastructure development and emergency management centers due to their relative safety from hydrological threats. Further risks include threat to food security, urban expansion and climate adaptation (Akinkuolie et al, 2025; Twum & Abubakari, 2019).

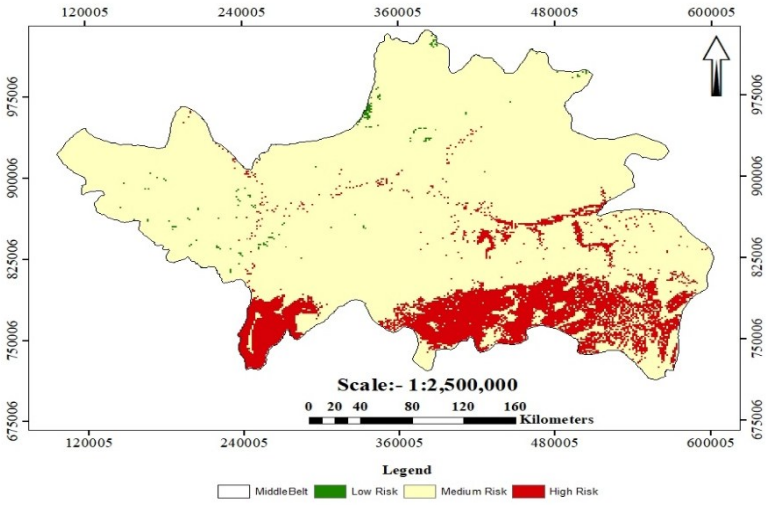


Figure 10: Flood Risk Map

Accuracy Assessment

The majority of GPS-recorded historical flood points fell within the high-risk zones, Medium-risk zones near river corridors and minimal flood points were located within low-risk areas

thereby confirming good predictive capability. Approximately one-third of the study area was classified as Wet Land. With the wet land areas showing a strong overlap with low elevation regions, low slope zones and river-adjacent areas. This confirms that NDWI effectively captured surface moisture conditions consistent with flood vulnerability.

The Flood Risk model demonstrates a strong spatial coherence, logical hydrological consistency, good agreement with field-observed flood points and multi-dataset convergence toward similar high-risk areas. The distribution of risk categories (dominantly medium risk with concentrated high-risk corridors) reflects realistic floodplain geomorphology in the region.

CONCLUSION

This paper demonstrates the effectiveness of geospatial modeling in identifying and analyzing flood-induced land degradation in the Middle Belt of Nigeria. By combining remotely sensed data with ground-truthing techniques and GIS-based MCDA, the study established spatial patterns of flood vulnerability and identified critical risk zones.

The findings confirm that topography (elevation and slope), land use characteristics, rainfall intensity, and hydrological proximity are significant drivers of flood-induced degradation. The use of NDWI and LULC maps not only enhanced flood detection but also offered insights into landscape dynamics and moisture variability. The study successfully produced a composite flood risk map, which serves as a strategic planning tool for urban developers, disaster management agencies, and policymakers.

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