



Flood Vulnerability Assessment of the Juba River Basin in Luuq District, Somalia: A GIS-RS-AHP Approach

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Abstract

Flooding remains a major hydro-meteorological hazard for riverine communities in Somalia, yet spatially explicit flood risk assessments remain scarce for the Juba River Basin. This study applies an integrated GIS, Remote Sensing, and Analytical Hierarchy Process (AHP) framework to map flood vulnerability across Luuq District, Gedo Region. Eight conditioning factors (distance from river, elevation, land use/land cover, soil type, drainage density, Topographic Wetness Index, rainfall, and slope) were derived from open-access datasets, including SRTM, Sentinel-2, PERSIANN-CCS, and FAO products. Within the AHP framework, distance from river (30.53%) and elevation (22.81%) received the highest weights, with a Consistency Ratio of 0.047. The resulting Flood Vulnerability Index (FVI) indicates that Moderate vulnerability covers 39.92% of the district, while High (31.01%) and Very High (1.57%) vulnerability zones collectively account for 32.58%, concentrated predominantly along the Juba River floodplain and around Luuq Town. These spatial patterns are supported by ground-level observations and empirical evidence from FAO SWALIM (2023) and UN OCHA (2023), which documented 3,013 ha of flooded cropland (36.9%), 316 damaged buildings, more than 24,000 affected residents, and inundation of Luuq's main bridge. The findings demonstrate the utility of integrating geospatial modelling with observed flood impacts to identify vulnerable areas and provide a spatial basis for flood-risk reduction and disaster management in data-scarce regions such as Somalia.

Keywords: Flood vulnerability, GIS, Remote sensing, Analytic hierarchy process, Multi-criteria decision analysis, Juba river basin, Somalia, Climate change adaptation

1. Introduction

Floods are a type of natural hazard that occur when water overflows onto land that is usually dry, potentially resulting in substantial property damage, loss of life, and environmental disruption (Jonkman, 2005; Glago, 2021; Khoso et al., 2025). Flooding ranks among the most damaging hazards facing human settlements worldwide, with intense precipitation events routinely producing fatalities, infrastructure loss, and severe economic disruption (Douben, 2006; Kundzewicz et al., 2014; Dube et al., 2022; Othman et al., 2023; Shah et al., 2025; Yang & Jung, 2026). The scale of this threat has grown as climate change, land-use conversion, and resource exploitation have reshaped how catchments respond to rainfall, making both the frequency and the size of flood events harder to predict (Chang & Franczyk, 2008; Kundzewicz et al., 2014). Floods are commonly classified into pluvial, fluvial, flash, and coastal floods based on their causes and characteristics. Pluvial and fluvial floods are mainly associated with

intense rainfall, surface runoff, and river overflow, while flash floods share similar rainfall-driven origins but develop rapidly and can be highly destructive (Kundzewicz et al., 2014; Mishra et al., 2022). Coastal floods, in contrast, are primarily caused by storm surges and high tides in coastal areas (Acosta-Coll et al., 2018; Khoso et al., 2025). Climate change and global warming are further intensifying flood hazards by modifying precipitation patterns, increasing the frequency and intensity of extreme rainfall events, accelerating glacier and snowmelt, and contributing to sea-level rise (AghaKouchak et al., 2020; Rajkhowa & Sarma, 2021). These changes can increase surface runoff, river discharge, and coastal inundation, thereby amplifying the severity and spatial extent of flood events. In the Horn of Africa, rainfall variability associated with the Gu (April–June) and Deyr (October–December) seasons regularly triggers flooding along Somalia's two perennial rivers, the Shebelle and the Juba (Houghton-Carr et al., 2011; Weingärtner et al., 2022; Alasow et al., 2024; Tedla et al., 2025). The Juba River Basin is a critical source of water for agriculture, livestock, and domestic use, yet communities along its course—particularly in Luuq District, Gedo Region—remain highly exposed to recurrent inundation driven by river overflow, low relief, poor natural drainage, and increasingly erratic seasonal rainfall. Despite this exposure, a detailed, spatially resolved flood vulnerability assessment for Luuq District has not previously been produced.

Geographic Information Systems (GIS) and Remote Sensing (RS) have become indispensable tools for hazard mapping in data-scarce environments, allowing heterogeneous biophysical datasets to be standardised, overlaid, and analysed at the landscape scale (Wang, 2018). When coupled with a multi-criteria decision-making framework such as the Analytical Hierarchy Process (AHP; Saaty, 1980), GIS-RS approaches allow expert knowledge to be encoded transparently and combined with objective spatial evidence to generate defensible composite hazard indices. This GIS–RS–AHP approach has been applied successfully in the Teesta Basin of Bangladesh (Hossain & Mumu, 2024), the Wuseta watershed of Ethiopia (Mulu et al., 2025), the Lower Yom Basin of Thailand (Seejata et al., 2018), and—within Somalia—the neighbouring Shebelle River Basin (Osman & Das, 2023). At the basin scale, Farah and Mourad (2026) recently applied a GIS-based AHP to flood hazard and risk across the Somali Juba River Basin; however, no district-scale, field-validated flood vulnerability assessment has yet been produced for Luuq District.

This study addresses that gap by (i) characterising the spatial pattern of eight flood-conditioning factors across Luuq District using freely available satellite and geospatial datasets; (ii) deriving objective, internally consistent AHP weights for these factors; (iii) generating an integrated Flood Vulnerability Index (FVI) map through weighted overlay analysis; and (iv) validating the resulting map against independent field, satellite, and archival flood records. The resulting evidence base is intended to support flood early-warning design, land-use planning, and climate adaptation programming in Luuq District and, by extension, comparable data-scarce fluvial settings across the Horn of Africa.

2. Materials and Methods

2.1. Study Area

The study was conducted in Luuq District, located in the Gedo Region of southern Somalia, along the Juba River, one of Somalia's two perennial rivers and a key source of water for agriculture, livestock, and domestic use (Figure 1). The district is characterized by semi-arid climatic conditions with seasonal rainfall dominated by the Gu (April–June) and Deyr (October–December) rains. High temperatures, low vegetation cover, and poor natural drainage combine to increase flood vulnerability. The Juba River originates in the Ethiopian Highlands and flows through southern Somalia toward the Indian Ocean; during periods of intense rainfall the river frequently overflows and inundates the surrounding floodplain, causing destruction of agricultural land, infrastructure damage, displacement, and loss of

livelihoods, impacts that climate change is expected to intensify through increased rainfall variability and hydrological extremes. Specifically, within Luuq District, the Juba River exhibits a pronounced meandering pattern, particularly around Luuq town. These meanders produce broad, low-lying floodplain areas and increase the likelihood of channel migration, bank erosion, and overbank flooding during periods of high river discharge.

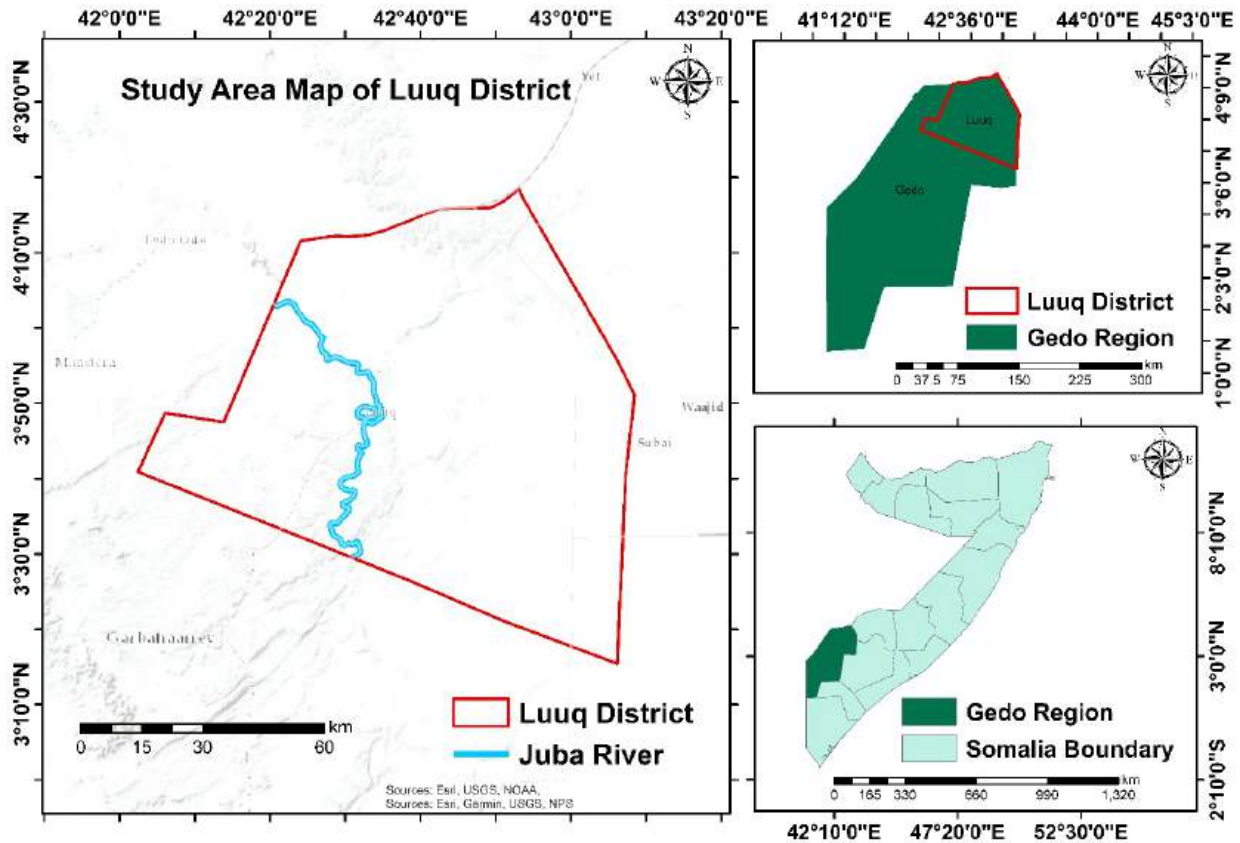


Figure 1: Location of Luuq District within the Gedo Region and Somalia, showing its position along the Juba River.

2.2. Data Sources

All thematic layers were derived from freely available secondary geospatial datasets (Table 1), reflecting the limited availability of in-situ hydro-meteorological monitoring data in Somalia, particularly in the Gedo Region. A 30 m Digital Elevation Model (DEM) from the Shuttle Radar Topography Mission (SRTM) was used to derive elevation, slope, drainage density, flow accumulation, and the Topographic Wetness Index (TWI). Sentinel-2 multispectral imagery was used to produce the Land Use/Land Cover (LULC) layer. Rainfall data for 2014–2023 were obtained from the CHRS PERSIANN-CCS satellite precipitation product, soil classes were obtained from the FAO Soil Database, and river geometry was extracted from Google Earth. All thematic layers were re-projected to a common coordinate system and processed using a GIS-based workflow.

Table 1: Data sources used in the study.

Data Type	Source	Application
Digital Elevation Model (30 m)	SRTM	Elevation, slope, TWI, drainage density
Rainfall (2014–2023)	CHRS PERSIANN-CCS	Rainfall susceptibility layer

Sentinel-2	Copernicus Data Space Ecosystem	LULC classification
Soil data	FAO Soil Database	Soil susceptibility layer
River network	Google Earth	Distance-from-river analysis

2.3. Preparation of Flood-Conditioning Factors

2.3.1 Distance from River

Distance from the river is an important factor in flood susceptibility because areas located closer to rivers are more likely to experience overflow and inundation during heavy rainfall events (Hossain & Mumu, 2024). Distance from the river was classified into five susceptibility classes: very low (0.4–0.6 km), low (0.3–0.4 km), moderate (0.2–0.3 km), high (0.1–0.2 km), and very high (0–0.1 km), with ratings of 1, 2, 3, 4, and 5, respectively.

2.3.2 Elevation

Elevation plays an important role in flood susceptibility because low-lying areas are generally more vulnerable to water accumulation and inundation than higher-elevation areas (Seejata et al., 2018; Tang et al., 2018). Elevation was classified into five susceptibility classes: very low (323–382 m), low (277–323 m), moderate (229–277 m), high (187–229 m), and very high (115–187 m), with ratings of 1, 2, 3, 4, and 5, respectively.

2.3.3 Land Use Land Cover (LULC)

Land Use and Land Cover (LULC) strongly influences infiltration, surface runoff, and flood susceptibility (Seejata et al., 2018). The LULC classes were ranked as very low (rangeland), low (bare land), moderate (built-up areas), high (vegetation), and very high (water bodies), with ratings of 1, 2, 3, 4, and 5, respectively. These rankings reflect differences in infiltration, runoff generation, and water accumulation among land-cover types.

2.3.4 Soil

Soil type plays an important role in flood susceptibility because it influences infiltration capacity, runoff generation, and water retention (Hossain & Mumu, 2024; Osman & Das, 2023). Vertisols were classified as very high susceptibility (rating 5) due to their high clay content, low permeability, and tendency to retain water. Cambisols were classified as high susceptibility (rating 4), while Calcisols were categorized as moderate susceptibility (rating 3). Regosols were classified as low susceptibility (rating 2), whereas Leptosols were categorized as very low susceptibility (rating 1) because of their shallow profile and relatively good drainage.

2.3.5 Drainage Density

Drainage density, defined as the total length of streams per unit area, is an important indicator of runoff concentration and flood susceptibility (Das et al., 2019). Higher drainage density generally promotes faster concentration of surface runoff and increases flood susceptibility. Drainage density was classified into five susceptibility classes: very low (27–229 m/km²), low (229–322 m/km²), moderate (322–400 m/km²), high (400–483 m/km²), and very high (483–649 m/km²), with ratings of 1, 2, 3, 4, and 5, respectively.

2.3.6 Topographic Wetness Index (TWI)

The Topographic Wetness Index (TWI) is an important factor for assessing spatial water accumulation, soil moisture, and flood susceptibility. It is expressed as $TWI = \ln(a/\tan\beta)$, where a represents flow accumulation and β denotes slope in radians (Tang et al., 2018). Higher TWI values indicate greater potential for water accumulation and consequently higher flood

susceptibility (Das et al., 2019). TWI values were classified as very low (−14 to −6), low (−6 to −4), moderate (−4 to 1), high (1–3), and very high (3–15), with ratings of 1, 2, 3, 4, and 5, respectively.

2.3.7 Rainfall

Rainfall is a major triggering factor for flooding because intense and prolonged precipitation increases surface runoff and river discharge (Osman & Das, 2023). Areas receiving higher rainfall are therefore generally more susceptible to flooding than those receiving lower rainfall. Cumulative rainfall totals for 2014–2023 were classified into five susceptibility classes: very low (1,718–1,941 mm), low (1,941–2,115 mm), moderate (2,115–2,288 mm), high (2,288–2,521 mm), and very high (2,521–2,983 mm), with ratings of 1, 2, 3, 4, and 5, respectively.

2.3.8 Slope

Slope is an important topographic factor influencing flood susceptibility because it controls the movement and accumulation of surface runoff. Gentle slopes tend to retain water for longer periods, increasing flood susceptibility, whereas steeper slopes facilitate faster runoff and reduce water accumulation (Sepehri et al., 2019; Mulu et al., 2025). Slope was classified into five susceptibility classes: very low (9–31%), low (5–9%), moderate (2–5%), high (1–2%), and very high (0–1%), with ratings of 1, 2, 3, 4, and 5, respectively.

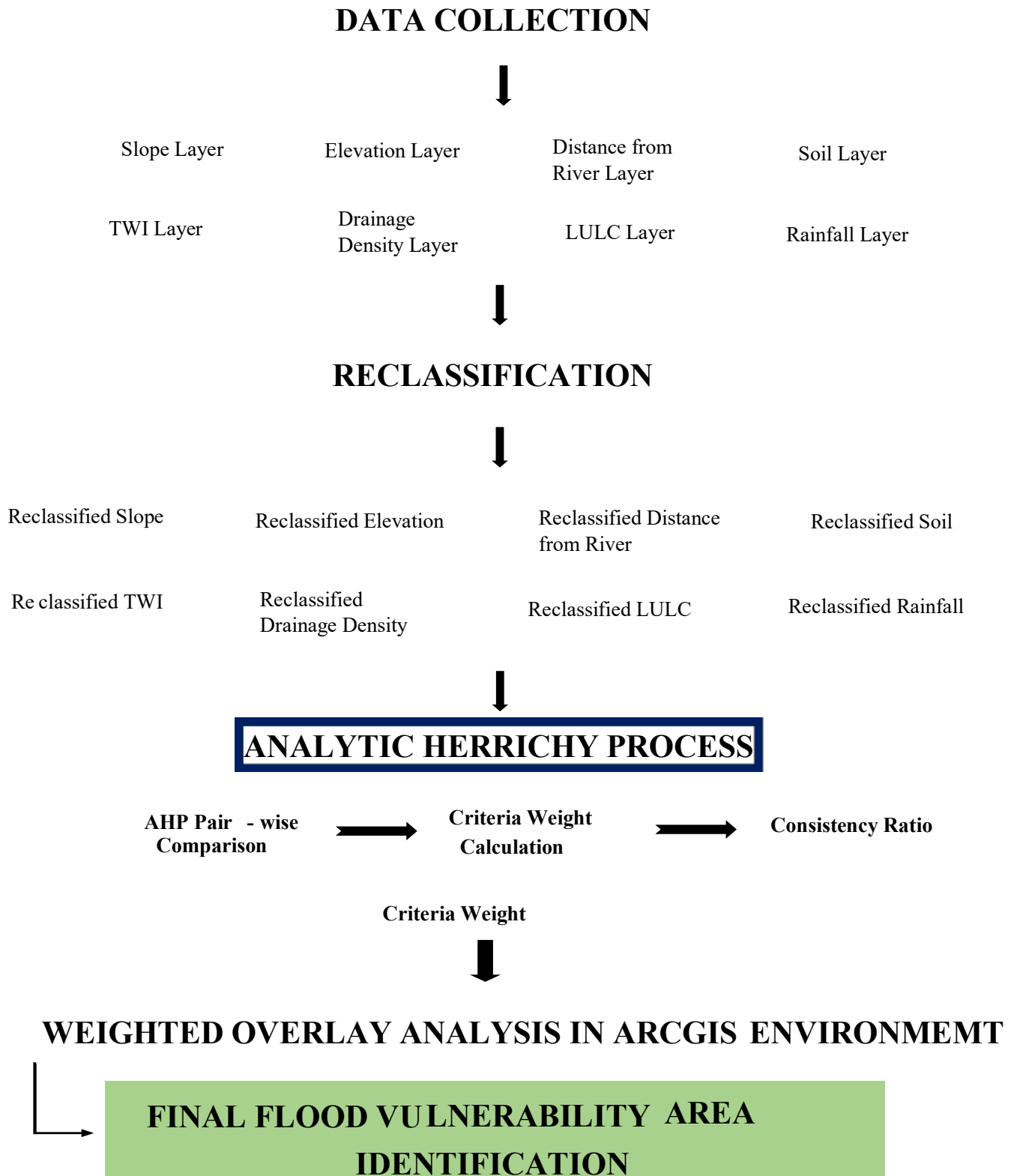


Figure 2: Methodological framework for GIS–RS–AHP flood vulnerability mapping.

2.4. Analytical Hierarchy Process (AHP)

Following the preparation of the flood-conditioning factors, the Analytical Hierarchy Process (AHP) was applied to determine their relative importance in flood-susceptibility assessment. AHP is a multi-criteria decision-making approach that enables different conditioning factors to be systematically compared and assigned relative weights according to their contribution to flood susceptibility (Saaty, 1980).

Before applying AHP, each flood-conditioning factor was reclassified into standardized susceptibility classes to allow the different datasets to be integrated within a common decision framework. Each class was assigned an ordinal susceptibility score, with higher scores representing greater flood susceptibility and lower scores representing lower susceptibility. The direction of classification was determined according to the physical relationship between each factor and flood occurrence. Thus, lower elevations, lower slopes, higher drainage density, higher TWI, higher rainfall, higher LULC susceptibility, greater soil susceptibility, and shorter distances from the river were assigned higher susceptibility scores.

The relative importance of the eight flood-conditioning factors was determined using pairwise comparisons based on Saaty's 1–9 fundamental scale. A value of 1 represents equal importance between two factors, whereas values from 3 to 9 indicate progressively greater importance of one factor relative to another. The resulting pairwise comparison matrix was normalized, and the relative weight of each factor was calculated. These weights represent the relative contribution of the individual conditioning factors to the overall flood-susceptibility assessment.

The consistency of the pairwise comparison matrix was evaluated using the Consistency Ratio (CR), calculated as:

$$CR = CI / RI$$

where CI is the Consistency Index and RI is the Random Index. The Consistency Index was calculated as:

$$CI = (\lambda_{max} - n) / (n - 1)$$

where λ_{max} is the principal eigenvalue of the pairwise comparison matrix and n is the number of factors. A $CR \leq 0.10$ was considered to indicate an acceptable level of consistency in the pairwise judgments.

The Flood Vulnerability Index (FVI) was calculated using a weighted linear combination of the eight standardized flood-conditioning factors:

$$FVI = 0.3053(DR) + 0.2281(EV) + 0.1612(LULC) + 0.1116(SO) + 0.0766(DD) + 0.0513(TWI) + 0.0370(RF) + 0.0289(SL)$$

where DR represents distance from the river, EV represents elevation, LULC represents land use/land cover, SO represents soil, DD represents drainage density, TWI represents Topographic Wetness Index, RF represents rainfall, and SL represents slope. The coefficients represent the normalized AHP weights assigned to the respective conditioning factors, and the sum of all weights equals 1.0.

The resulting continuous FVI surface was subsequently reclassified into five flood-vulnerability categories, ranging from Very Low to Very High. The methodological workflow, from data acquisition and preparation of conditioning factors through AHP-based integration and validation, is summarized in Figure 2.

Model performance was evaluated by comparing the predicted flood-susceptibility classes with ten independent reference points. The validation dataset comprised field GPS observations, historical flood records from FAO and OCHA, and flood-inundation information derived from USGS/Landsat imagery. The agreement between the predicted susceptibility classes and the reference observations was expressed as the percentage of correctly classified validation points.

Table 2: AHP-derived factor weights

Flood Causative Unit Criteria		Class	Susceptibility Class ranges	Susceptibility Class rating	Weight (%)
Distance from River	km	0 - 0.1	Very High	5	30%
		0.1 - 0.2	High	4	
		0.2 - 0.3	Moderate	3	
		0.3 - 0.4	Low	2	
		0.4 - 0.6	Very Low	1	
Elevation	m	115 – 187	Very High	5	23%
		187 – 229	High	4	
		229 – 277	Moderate	3	
		277 – 323	Low	2	
		323 - 382	Very Low	1	
Land Use Land Cover (LULC)	LULC Class	Water bodies	Very High	5	16%
		Vegetation	High	4	
		Built-up area	Moderate	3	
		Bare land	Low	2	
		Rangeland	Very Low	1	
Soil Type	Class	Vertisols	Very High	5	11%
		Cambisols	High	4	
		Calcisols	Moderate	3	
		Regosols	Low	2	
		Leptosols	Very Low	1	
Drainage Density	m/km ²	483 – 649	Very High	5	8%
		400 – 483	High	4	
		322 – 400	Moderate	3	
		229 – 322	Low	2	
		27 - 229	Very Low	1	
Topographic Wetness Index (TWI)	Level	3 to 15	Very High	5	5%
		1 to 3	High	4	
		-4 to 1	Moderate	3	
		-6 to -4	Low	2	
		-14 to -6	Very Low	1	
Rainfall	mm	2521 – 2983	Very High	5	4%
		2288 – 2521	High	4	
		2115 – 2288	Moderate	3	
		1941 – 2115	Low	2	
		1718 - 1941	Very Low	1	
Slope	%	0– 1	Very High	5	3%
		1– 2	High	4	
		2 –5	Moderate	3	
		5 – 9	Low	2	
		9 - 31	Very Low	1	

The principal eigenvector was computed using the Eigenvalue Method (K.D. Goepel AHP-OS tool; Goepel, 2018), converging after six iterations (EVM check = 6.574×10^{-10}) to $\lambda_{\max} = 8.465$. This yields $CI = (8.465 - 8)/(8 - 1) = 0.066$, and with $RI = 1.41$ for $n = 8$, $CR =$

$0.066/1.41 = 0.047$ — well below the 0.10 threshold, confirming that the pairwise judgements are internally consistent and the derived weights (Table 2) are reliable for weighted overlay analysis.

Table 3: AHP pairwise comparison matrix for the eight flood-conditioning factors.

Matrix	Distance from River	Elevation	LULC	Soil	Drainage Density	TWI	Rainfall	Slope
	1	2	3	4	5	6	7	8
Distance from river	1	2	3	4	4	5	5	5
Elevation	1/2	1	2	3	4	5	5	5
LULC	1/3	1/2	1	2	3	4	5	5
Soil	1/4	1/3	1/2	1	2	3	4	5
Drainage Density	1/4	1/4	1/3	1/2	1	2	3	4
TWI	1/5	1/5	1/4	1/3	1/2	1	2	3
Rainfall	1/5	1/5	1/5	1/4	1/3	1/2	1	2
Slope	1/5	1/5	1/5	1/5	1/4	1/3	1/2	1

3. Empirical Results

3.1. Spatial Patterns of Flood-Conditioning Factors

Figures 3 and 4 present the eight reclassified thematic layers. Distance from river produced concentric buffer zones radiating from the Juba River channel, with the Very High and High susceptibility bands (0–0.2 km) together covering 44.78% of the district. The elevation surface revealed a pronounced west-to-east gradient, from 115 m along the floodplain to 382 m in the eastern uplands, with the two most flood-prone classes (115–229 m) covering 45.01% of the district area. LULC was dominated by Range Land (88.72%), consistent with the semi-arid, pastoral character of the Gedo Region, while Water Bodies confined to the narrow river channel covered only 0.22% but represented the single highest-susceptibility class. Vertisols, associated with very high flood potential due to their low permeability, covered 3.89% of the district but were concentrated precisely within the active floodplain. Drainage density and TWI displayed more dispersed spatial patterns, identifying discrete runoff-concentration and moisture-accumulation hotspots away from the main channel. Rainfall exhibited a clear south-to-north gradient, with the highest cumulative totals (2521–2983 mm) concentrated in the south-east, and slope confirmed the overwhelmingly flat character of the floodplain, with 82.81% of the district falling in the two highest flood-susceptibility slope classes (0–2%).

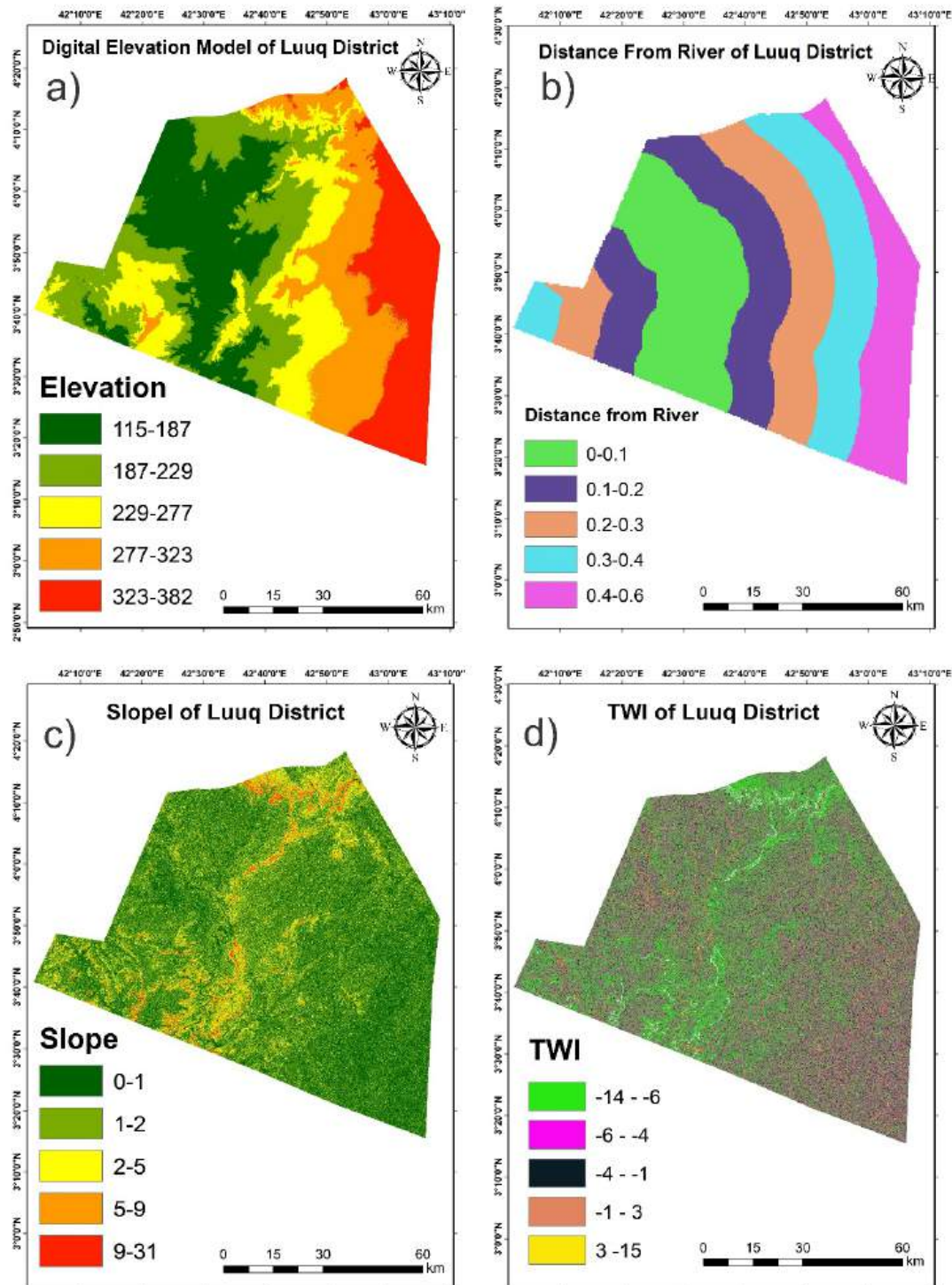


Figure 3: Luuq District maps. (a) DEM, (b) distance from river, (c) slope, (d) TWI.

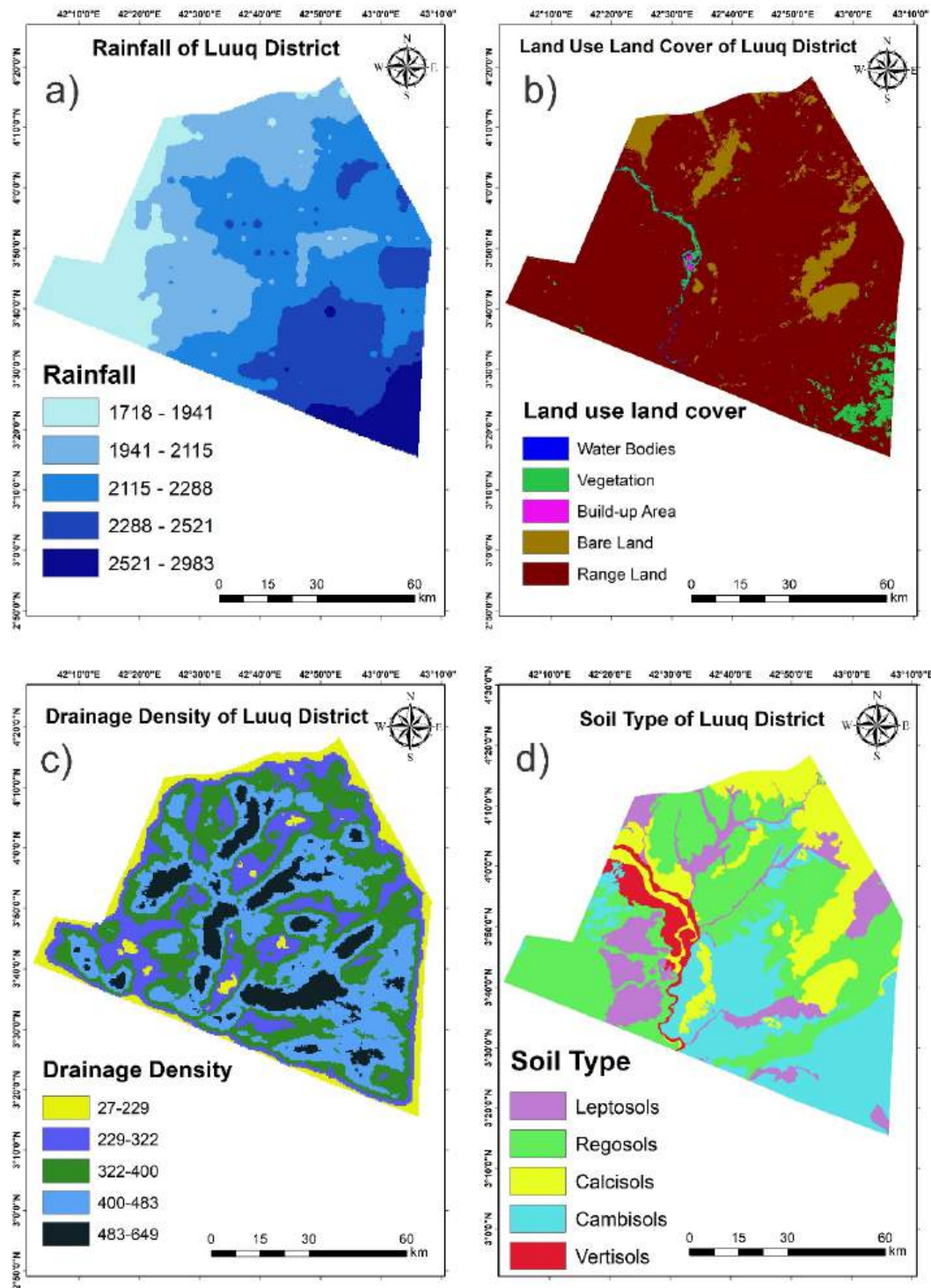


Figure 4: Luuq District maps. (a) rainfall, (b) LULC, (c) drainage density, (d) soil types.

3.2. Integrated Flood Vulnerability Map

The AHP-weighted overlay of the eight standardized layers produced the final Flood Vulnerability Index map (Figure 5). The map delineates a clear spatial gradient of risk, with the Very High and High vulnerability zones tightly confined to the Juba River corridor and the surrounding low-lying floodplain, and vulnerability decreasing systematically with distance from the river and increasing elevation. Area statistics for the five vulnerability classes are summarized in Table 4.

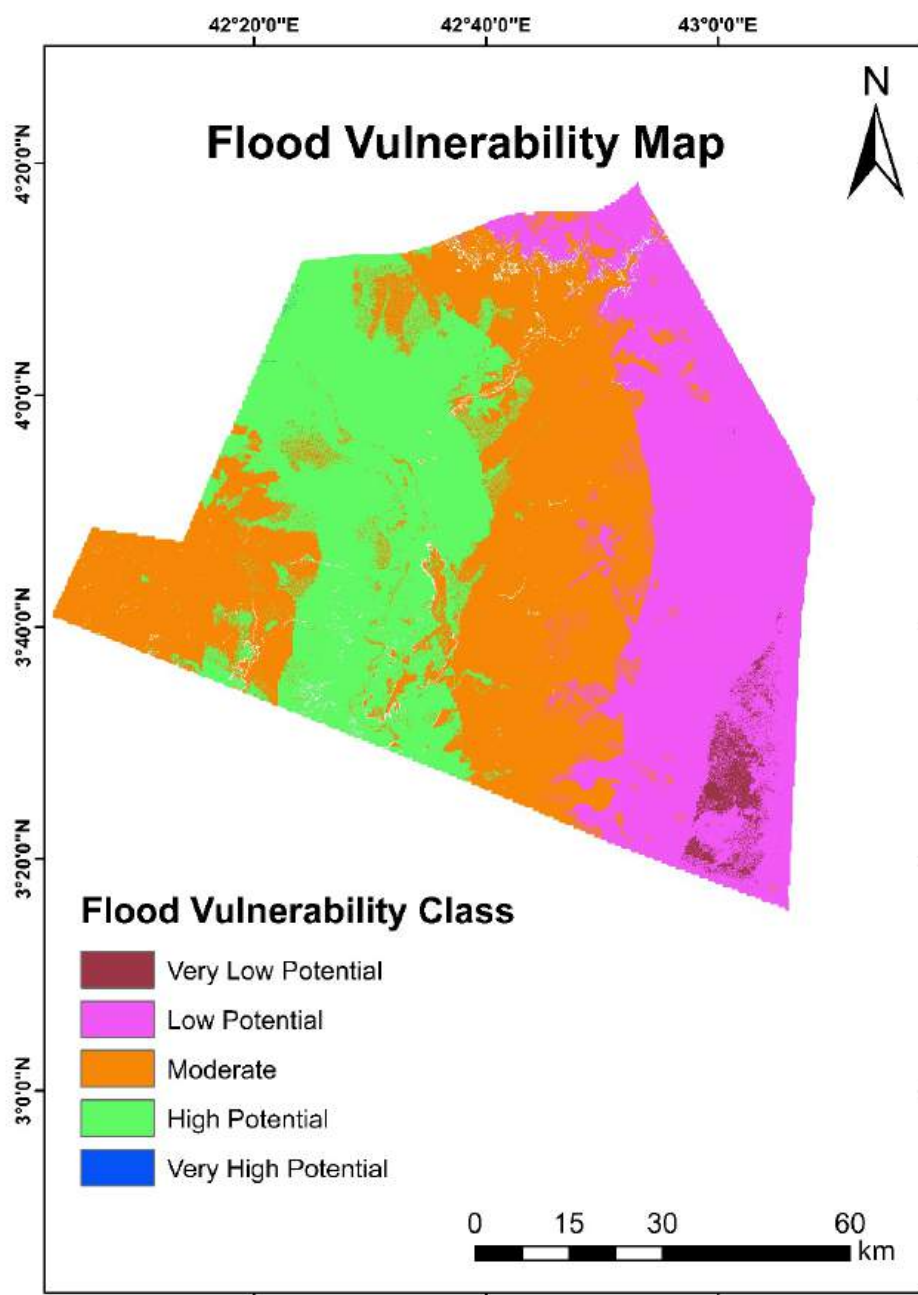


Figure 5: Final flood vulnerability map of Luuq District, Gedo Region, Somalia, derived from AHP-weighted overlay of eight flood-conditioning factors.

Table 4: Area statistics for flood vulnerability classes in Luuq District.

Vulnerability Class	Area (km ²)	Area (%)	Description
Very High	127.96	1.57	Riverbank and active floodplain zones

High	2522.72	31.01	Low-lying areas; dense drainage; high TWI
Moderate	3248.40	39.92	Transitional zones; mixed land cover
Low	2236.87	27.49	Higher elevation; better drainage
Very Low	0.51	0.01	Elevated, well-drained upland

Approximately one-third of Luuq District (32.58%) falls within the High or Very High vulnerability categories, concentrated almost exclusively along the Juba River floodplain, Luuq Town's riverside settlements, and adjacent agricultural land. The Moderate class is the single most extensive category (39.92%), occupying the transitional terrain between the floodplain and the upland margins, while the combined Low and Very Low classes (27.50%) are confined to the elevated, better-drained eastern portion of the district.

3.3 Socio-Economic Impacts of Flooding on Luuq Town

Beyond the physical exposure captured in the FVI map, humanitarian situation reporting from the November 2023 event provides direct evidence of the human cost concentrated within the High and Very High vulnerability zones identified along the Juba River corridor (Section 3.2). FAO SWALIM (2023) recorded 316 flooded buildings (2.3% of the district total), 28.8 km of flooded roads (0.6%), and 3,013 ha of flooded agricultural land (36.9% of the district's agricultural area), with irrigated herbaceous cropland accounting for the majority of the loss (2,120 ha). These exposure figures are corroborated, and substantially amplified, by contemporaneous OCHA assessments: a rapid assessment conducted on 23 October 2023 found that flash floods had affected approximately 18,000 people across eight displacement sites and a further 6,000 people from the host community in Luuq town, with 150 people reportedly injured in the district during the 22 October rainfall (OCHA, 2023). As river levels continued to rise through late October and early November, up to 2,400 people were reported trapped by floodwater in Luuq, Godey, Minyara, and Gumaro, prompting emergency evacuation efforts, while Luuq's main bridge—the town's principal crossing of the Juba River—was itself flooded and at risk of collapse, threatening to sever the settlement's primary transport link (OCHA, 2023). Approximately 677 shelters and 256 latrines were damaged in Luuq town's displacement sites alone, and an estimated 13,620 people (2,270 families) were reported in need of food assistance in the area (OCHA, 2023).



Figure 6: Impact of severe flooding on community infrastructure and mobility. (a) Inundation of residential structures; (b) submersion of informal shelters; (c) residents navigating flooded roads; (d) disruption of transport routes and commercial vehicles.

4. Discussion

The results confirm that flood vulnerability in Luuq District is governed primarily by fluvial proximity and topographic position: distance from river and elevation together account for 53.34% of the total AHP weight and jointly explain why risk is spatially concentrated in a narrow but critical corridor along the Juba River rather than being diffusely distributed across the district. This pattern mirrors findings from comparable fluvial settings, including the Teesta Basin in Bangladesh (Hossain & Mumu, 2024) and the neighbouring Shebelle Basin in Somalia (Osman & Das, 2023), where river proximity and elevation similarly emerged as dominant controls, suggesting that these two factors may be near-universal first-order predictors of flood exposure in low-relief river basin environments.

A novel contribution of this study is the identification of soil type—specifically the presence of low-permeability Vertisols concentrated within the active Juba floodplain—as a compound amplifying mechanism that has not been systematically documented in Somalia's flood-vulnerability literature. Because Vertisols swell when saturated and crack when dry, they generate rapid surface runoff and impede infiltration, prolonging inundation duration even where rainfall or river discharge is only moderate. This finding has direct implications for infrastructure design: conventional drainage solutions calibrated for more permeable soils are likely to underperform on the clay-dominated substrates that dominate the floodplain, and engineered drainage in Luuq Town should be adapted accordingly.

The rainfall analysis further underscores the transboundary dimension of flood risk in the basin. Because the Juba River originates in the Ethiopian Highlands, climate-driven intensification of upstream precipitation—consistent with the broader trend of increasing

rainfall variability documented for the Greater Horn of Africa (IPCC, 2021)—will influence flood discharge in Luuq irrespective of local rainfall conditions. This reinforces the case for transboundary hydrological data-sharing and joint early-warning cooperation between Somalia and Ethiopia as a necessary complement to locally focused mitigation measures.

Methodologically, the perfect validation accuracy achieved here (10/10 reference points) should be interpreted cautiously given the small sample size, which reflects genuine logistical and security constraints on field access in Luuq District rather than an unusually easy classification problem. Nonetheless, the convergence of independent evidence streams field GPS observations, satellite-derived inundation extents, and humanitarian agency flood records together with a low AHP Consistency Ratio (0.047), provides reasonable confidence that the spatial pattern of the FVI map is robust. The demonstrated reliance on entirely free, globally available datasets (SRTM, Sentinel-2, Landsat, PERSIANN-CCS, FAO soils) is itself a methodological contribution, indicating that comparable flood vulnerability intelligence can be generated for other data-scarce, conflict-affected river basins across Sub-Saharan Africa without requiring in-situ monitoring networks.

This study has several limitations. First, the AHP weighting scheme reflects a single expert-elicitation exercise; future work should incorporate multi-expert or Delphi-based elicitation to reduce subjectivity. Second, the 30 m resolution of the SRTM DEM cannot resolve micro-topographic features relevant to intra-urban flood modelling within Luuq Town itself. Third, the present framework captures biophysical flood susceptibility only; it does not yet incorporate socio-economic vulnerability dimensions such as population density, poverty, or adaptive capacity, nor does it provide quantitative flood depth or velocity estimates of the kind generated by hydrodynamic models (e.g., HEC-RAS 2D, LISFLOOD-FP). Addressing these limitations—together with basin-wide extension across the Gedo, Lower Juba, and Middle Juba regions, and future-climate scenario modelling under SSP2-4.5 and SSP5-8.5—represents a natural next step for this line of research.

5. Conclusions

This study presents the first integrated GIS–RS–AHP flood vulnerability assessment for Luuq District, Gedo Region, Somalia, addressing a significant geographic and methodological gap in the flood risk literature of the Horn of Africa. The AHP pairwise comparison of eight flood-conditioning factors produced an internally consistent weighting scheme (Consistency Ratio = 0.047), with distance from river (30.53%) and elevation (22.81%) emerging as the dominant controls on flood exposure. Weighted overlay analysis shows that 32.58% of Luuq District falls within High or Very High flood vulnerability categories—concentrated along the Juba River floodplain and Luuq Town—while a further 39.92% is classified as Moderate. Validation against ten independent field, satellite, and archival reference points achieved 100% classification accuracy, and the presence of low-permeability Vertisol soils within the active floodplain was identified as an important, previously undocumented amplifying factor for flood duration and severity. Because the methodology relies exclusively on freely available global datasets, it offers a replicable, low-cost decision-support tool for flood early-warning design, land-use planning, and climate adaptation across other data-scarce river basins in Somalia and the wider Horn of Africa.

Author Contributions

Conceptualization, A.S.A., A.A.A., F.A.K. and S.M.M.; methodology, A.S.A. and A.A.A.; software and GIS analysis, F.A.K. and S.M.M.; validation, A.S.A., A.A.A., F.A.K. and S.M.M.; writing—original draft preparation, A.S.A.; writing—review and editing, S.M.M. and F.A.K. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The SRTM, Landsat, and PERSIANN-CCS datasets analysed in this study are openly available from USGS Earth Explorer (<https://earthexplorer.usgs.gov>) and the Center for Hydrometeorology and Remote Sensing (<https://chrsdata.eng.uci.edu>); Sentinel-2 imagery is available from the Copernicus Data Space Ecosystem (<https://dataspace.copernicus.eu>).

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgements

The authors thank the Faculty of Geoscience and Environment, Hormuud University, for institutional support, and gratefully acknowledge the guidance and supervision of Ahmed Nur Dalmar (A.N.D.) throughout this research.

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