

Article

Ensemble Multi-Criteria Flood Susceptibility Modelling with Spatial Uncertainty Quantification: A Provincial-Scale Application in KwaZulu-Natal, South Africa

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Abstract

Flooding remains a major hydro-meteorological hazard in KwaZulu-Natal, yet province-wide susceptibility assessments incorporating modelling uncertainty are limited. This study develops an ensemble multi-criteria flood susceptibility framework integrating Analytical Hierarchy Process (AHP), fuzzy logic transformation, and frequency ratio (FR) modelling within a cloud-based geospatial environment. Twelve hydro-geomorphological and environmental conditioning factors, including topography, rainfall, land cover, hydrology, and soil proxies, were normalized using percentile scaling. Three independent flood susceptibility models were generated and combined using ensemble mean aggregation, while pixel-wise standard deviation quantified spatial uncertainty. Model validation employed a 10-year historical flood inventory (2015–2025) comprising 65 documented flood locations. The ensemble flood susceptibility index (FSI) ranged from 0.05 to 1.00, with moderate susceptibility zones covering 51.08% of the province. High and very high susceptibility classes occupied 8.36%, indicating spatially concentrated but hydrologically significant risk hotspots. Uncertainty analysis showed low inter-model variability (0.00–0.11), demonstrating strong methodological stability. Validation results confirmed that 73.85% of historical flood points were located within high susceptibility zones, with over 90% captured within overall susceptible classes. The study introduces a hybrid deterministic–fuzzy–probabilistic ensemble modelling approach combined with pixel-level uncertainty mapping and scalable cloud computation. Findings support disaster risk reduction, urban and catchment planning, and early warning system optimization in flood-prone regions. The framework provides a transferable methodology for data-limited environments requiring reliable and uncertainty-aware flood hazard assessment.

Keywords: flood susceptibility mapping; analytical hierarchy process; frequency ratio flood damage and resilience; flood monitoring and warning systems; ensemble flood modelling

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1. Introduction

1.1. Background

Flooding remains one of the most pervasive and destructive hydrological hazards globally, driven by complex interactions between climate variability, catchment dynamics, and anthropogenic landscape change [1,2]. Extreme precipitation events associated with a warming atmosphere are increasing flood frequency, magnitude, and spatial extents in many regions [3]. Floods have significant implications for watershed processes, infrastructure resilience, and socio-economic systems [4,5]. In southern Africa, and specifically within KwaZulu-Natal, recent flood events have highlighted the need for robust, process-based spatial flood susceptibility assessment at regional scales to support hazard mitigation, land-use planning and adaptive water resources management.

Flood susceptibility modelling seeks to quantify the predisposition of landscapes to inundation by integrating multiple hydro-geomorphological, climatic, and land surface controls [6]. Unlike event-specific hydraulic modelling, susceptibility approaches focus on intrinsic predisposition under a range of hydrological conditions. This process leverages spatially distributed conditioning factors to characterize flood-prone zones [7]. Key topographic and process indicators that include elevation, slope, drainage density, topographic wetness index (TWI), and flow accumulation exert primary controls on runoff generation, flow concentration, and inundation extent [8]. Climatic variables such as rainfall intensity and distribution further modulate flood responses within heterogeneous catchments, while land use and land cover dynamics influence surface roughness, infiltration capacity, and runoff routing behaviour [9,10]. The integration of these multi-scale controls into spatial flood susceptibility models advances hydrological understanding beyond simplistic representations of flood risk.

Multi-criteria decision analysis (MCDA) methods, particularly the Analytical Hierarchy Process (AHP), have long been employed to structure expert judgement in weighting flood conditioning factors [11–13]. AHP's pairwise comparison framework allows the inclusion of hydrological insight into factor weights, and its consistency metrics safeguard against illogical weighting schemes [14]. However, even with rigorous consistency control, deterministic MCDA remains inherently subjective, particularly in complex hydrological landscapes where interactions among driving factors are nonlinear and context-dependent [15]. Moreover, traditional MCDA methods may poorly capture threshold effects in hydrological responses or account for uncertainty in conditioning data, particularly under data limitations [16]. Recent studies continue to rely on standalone AHP and frequency ratio (FR) approaches that emphasize factor selection and relative weighting without explicitly addressing the uncertainty inherent in model structure. For example, recent GIS-based AHP and FR applications highlight susceptibility mapping efficiency but remain limited in uncertainty characterization and hydrological process interpretation [17].

Hybrid and ensemble modelling approaches are emerging to address these limitations, including works by Yilmaz [18] and Ghosh and Maiti [19]. Fuzzy logic methods extend traditional MCDA by transforming crisp weights into membership functions, accommodating gradual transitions in flood susceptibility thresholds [20]. When combined with AHP and FR, fuzzy logic offers enhanced representation of imprecise hydrological relationships. Hybrid fuzzy MCDA applications can exhibit sensitivity to arbitrary membership definition and lack robust uncertainty quantification [21]. More recently, ensemble modelling frameworks which integrate outputs from multiple base models and Artificial Intelligence (AI) logarithms have demonstrated good agreement with the available historical flood inventory and model generalizability [22,23]. In a West African flood susceptibility context, ensembles combining evidential belief functions, relative frequency

ratio, and Shannon entropy models achieved superior delineation of flood-prone zones by leveraging complementary strengths of constituent models, thereby reducing single-model bias [24].

From a hydrological perspective, explicit uncertainty quantification is critical [25]. Hydrological processes exhibit inherent variability across space and time, arising from scaling of precipitation, catchment response heterogeneity, and soil moisture dynamics, as well as from measurement and model structural uncertainty [26]. Pixel-level uncertainty mapping across ensemble outputs provides spatially explicit indicators of model agreement and confidence, enabling stakeholders to target areas of high susceptibility and high uncertainty for additional data collection or refined modelling [27].

Despite these methodological advances, key research gaps persist. Many existing studies focus primarily on classification performance metrics without providing comprehensive uncertainty fields that reflect model structural variability, while the hydrological interpretation of susceptibility outputs and the combined influence of topographic, climatological, and land cover factors remain underexplored. In addition, inconsistencies in the spatial resolution and harmonization of conditioning factors, together with the limited scalability of ensemble approaches in data-scarce regions, constrain operational application and cross-study comparability. To address these challenges, this study develops a cloud-based ensemble framework that integrates the Analytical Hierarchy Process (AHP), fuzzy logic, and frequency ratio (FR) modelling, alongside pixel-level uncertainty mapping, to produce an interpretable, and scalable flood susceptibility assessment for provincial-scale flood risk management.

1.2. Aim and Objectives

In response to the research gaps, this study aims to develop an ensemble multi-criteria flood susceptibility modelling framework integrating AHP-based weighted linear combination, fuzzy logic transformation, and a frequency ratio statistical configuration. By leveraging percentile-based factor normalization and optimal spatial resolution, the framework aims to balance hydrological detail with computational scalability. Ensemble outputs are synthesized into a robust susceptibility index, and pixel-wise inter-model variability is quantified to delineate uncertainty fields across the province. The framework's implementation in a cloud-computing environment facilitates reproducibility, responds directly to the identified research gaps by embedding uncertainty assessment and hydrological process emphasis into flood susceptibility modelling at a provincial scale. The specific objectives of this study are:

1. to construct a process-informed ensemble flood susceptibility framework integrating MCDA, fuzzy logic, and statistical methods,
2. to spatially quantify uncertainty arising from methodological variability; and
3. to assess the spatial distribution of flood susceptibility across KwaZulu-Natal to support hydrologically informed risk management.

By explicitly combining ensemble modelling, uncertainty quantification, and hydrological interpretation within a unified framework, this study advances regional flood susceptibility assessment and supports evidence-based water resources and hazard planning.

2. Materials and Methods

2.1. Study Area

This study was conducted in KwaZulu-Natal Province of South Africa (Figure 1). KwaZulu-Natal is located along the eastern seaboard of South Africa with the Indian Ocean forming its eastern boundary. The province exhibits pronounced topographic gradients, extending from the high elevations of the uKhahlamba–Drakensberg escarpment

in the west to undulating midlands and low-lying coastal plains in the east [28]. This altitudinal variation strongly controls its hydro-climatic regime. KwaZulu-Natal experiences a humid subtropical climate along the coast, transitioning to cooler temperate conditions in the interior highlands [29]. Rainfall is predominantly summer-dominant and often convective in nature, with marked spatial variability driven by orographic uplift and mesoscale storm systems [5]. Hydrologically, the province is characterized by dense and dissected river networks, including major systems such as the Tugela River and Umgeni River, which drain steep catchments toward the Indian Ocean, producing rapid runoff responses in upland areas and more attenuated flows across floodplains [30].

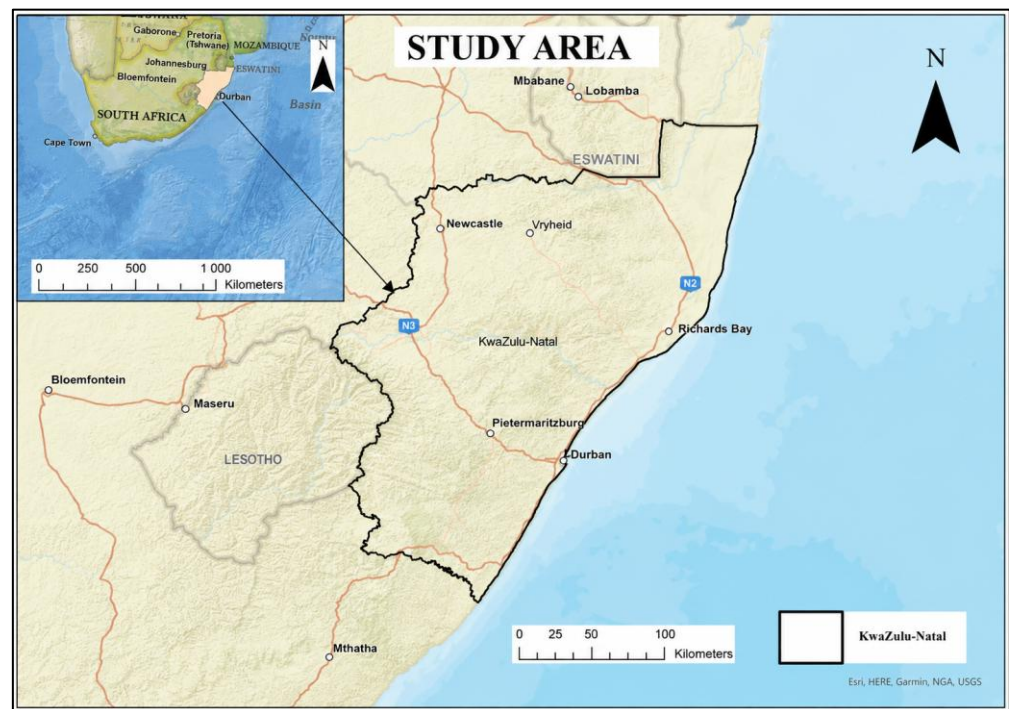


Figure 1. Study area: KwaZulu-Natal Province of South Africa.

Flooding is a major hydro-meteorological hazard in KwaZulu-Natal. Intense convective storms generate short-duration, high-intensity rainfall that interacts with steep terrain, shallow soils, and dense drainage networks to trigger flash floods, particularly across escarpment and midland catchments [31]. Low-gradient coastal plains are vulnerable to prolonged inundation due to backwater effects, elevated water tables, and estuarine influences. Historically, the province has experienced recurrent high-impact flood events, most notably the April 2022 floods, which highlighted escalating risk under combined climatic and land-use pressures [5,32]. These interacting processes warrant a modelling framework that can integrate multi-source spatial data, respect hydrological controls, and transparently quantify spatial uncertainty.

2.2. Delineation and Google Earth Engine Platform

The methodological framework for this study employs a multi-criteria decision analysis (MCDA) approach integrated with ensemble modelling within a Geographic Information System (GIS) environment implemented on the Google Earth Engine (GEE) cloud-computing platform. This approach aligns with established practices in flood susceptibility mapping, where MCDA enables the systematic integration of multiple flood conditioning factors [33], while ensemble modelling reduces model-specific bias and improves prediction accuracy [34].

The study area was delineated by extracting the boundary of the KwaZulu-Natal province from the FAO Global Administrative Unit Layers (GAUL) of the 2015 Level 1 administrative boundaries dataset for South Africa. This boundary served as the spatial mask for clipping all subsequent datasets, thereby ensuring analytical consistency across the provincial extent. The GEE platform was selected for its petabyte-scale data catalogue, parallel processing capabilities, and elimination of local storage and processing constraints [35].

2.3. Data Acquisition and Preprocessing

2.3.1. Data Sources

Twelve flood conditioning factors were derived from seven distinct satellite and modelled datasets, grouped into four thematic categories that included topography, hydrology, land use and land cover (LULC), climate, and soil with lithology proxies presented in Table 1.

Table 1. Summary of datasets used in flood susceptibility analysis.

Dataset	Source	Original Resolution	Temporal Coverage	Derived Factors
Administrative Boundaries	FAO/GAUL 2015 Level 1	N/A	2015	Study area mask
Digital Elevation Model (DEM)	NASA SRTMG	30 m	2000	Elevation, Slope, Curvature, TWI
Hydrography	MERIT Hydro v1.0.1	90 m (3 arc-second)	2019	Flow accumulation, Distance to rivers, Drainage density
Land Use & Land Cover (LULC)	Department of Forestry, Fisheries and the Environment (DFEE)	20 m	2022	LULC classes, Susceptibility scores
Satellite Imagery	Copernicus Sentinel-2 SR	10 m	2020–2023	NDVI (Vegetation index)
Rainfall	CHIRPS Daily	5 km	2010–2023	Mean annual rainfall
Soil/Lithology	Derived from slope	30 m	-	Soil proxy, Lithology proxy

2.3.2. Data Harmonization, Normalization and Standardization

Prior to normalization, all conditioning factors underwent systematic harmonization to resolve incompatibilities arising from heterogeneous data sources. The twelve factors originated from seven distinct datasets with spatial resolutions ranging from 10 m (Sentinel-2) to 5 km (CHIRPS rainfall) and temporal coverages spanning 2000 to 2023. All datasets were reprojected to WGS 84 (EPSG:4326) and resampled to a consistent 30 m resolution bilinear interpolation for continuous variables (elevation, slope, rainfall, TWI, flow accumulation) and nearest-neighbour interpolation for categorical variables (LULC). Temporal harmonization focused on the overlapping period 2010–2023 for climatic and vegetation indices, while recognizing that topographic and hydrological factors (DEM, MERIT Hydro) were treated as temporally invariant given their geomorphological stability over the study timeframe. Following harmonization, all factor layers were normalized to a consistent 0–1 range using a percentile-based approach that minimizes the influence of outliers.

2.4. Topographic Factor Analysis

Topographic factors were derived from the DEM at 30 m resolution. Four primary derivatives below were calculated.

2.4.1. Elevation

Raw elevation values in metres above sea level were extracted directly from the DEM in Figure 2. Lower elevations are typically associated with higher flood susceptibility due to downstream accumulation of runoff and proximity to base level [36].

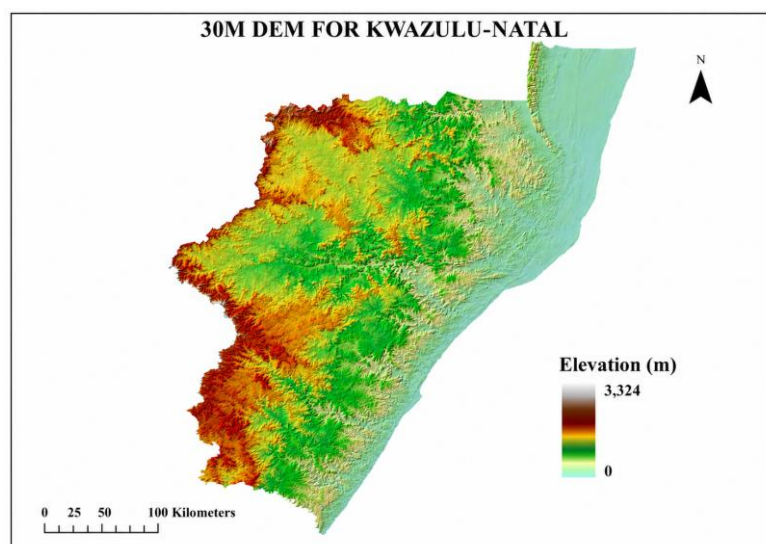


Figure 2. DEM of the KwaZulu-Natal.

2.4.2. Slope Gradient

Slope was computed using standard terrain analysis algorithms implementing a 3×3 moving window [37]. Slope, as presented in Figure 3, influences flood susceptibility through its control over overland flow velocity, infiltration rates, and surface runoff generation. Flat areas promote water accumulation and prolonged inundation, while steep terrain facilitates rapid runoff [38].

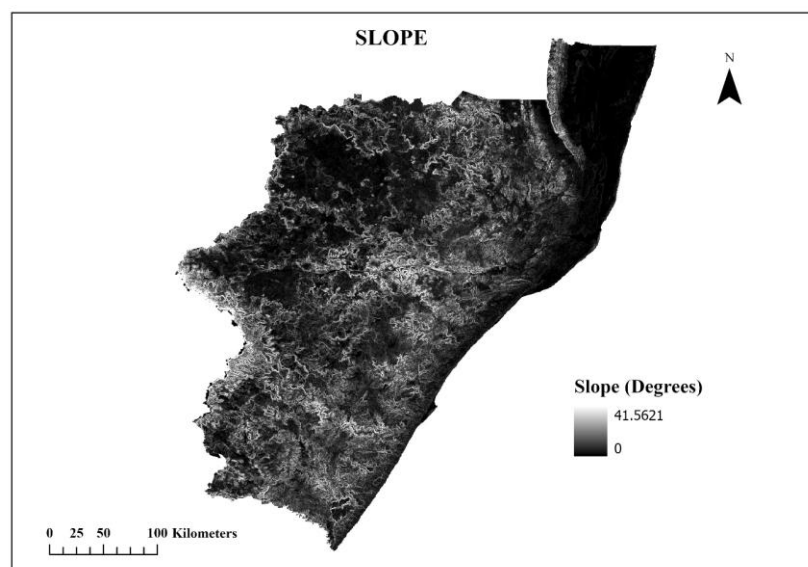


Figure 3. Slope map for KwaZulu-Natal.

2.4.3. Curvature

A curvature proxy in Figure 4 was generated by calculating the slope of the slope (second derivative of elevation), then multiplied by -1. This approximation identifies convex (positive) and concave (negative) terrain features, with concave areas (negative curvature) indicating topographic convergence and potential water accumulation zones [39].

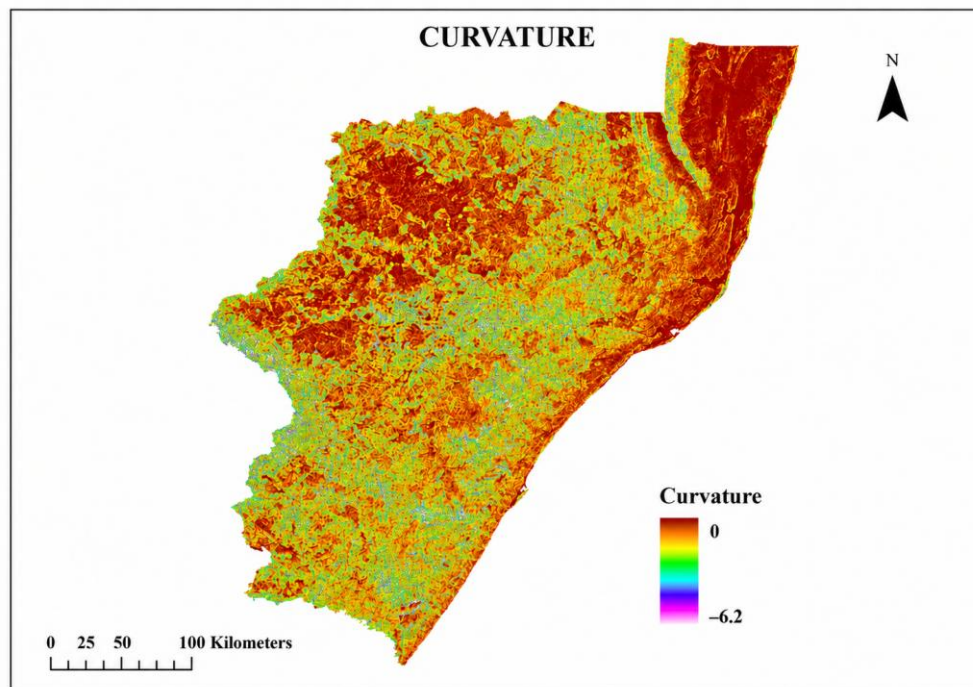


Figure 4. Curvature map for KwaZulu-Natal.

2.4.4. Topographic Wetness Index (TWI)

The topographic wetness index as a compound topographic attribute presented in Figure 5, was calculated as:

$$TWI = \ln \left(\frac{FlowAccumulation + 1}{\tan(Slope_{rad}) + 0.001} \right) \quad (1)$$

where FlowAccumulation represents the upstream contributing area and $Slope_{rad}$ is slope in radians. The 0.001 term prevents division by zero in flat areas. TWI quantifies the spatial distribution of soil moisture and saturation potential, with higher values indicating greater water accumulation [40].

2.5. Hydrological Factor Analysis

Hydrological factors were assessed using the MERIT Hydro dataset [41], a global hydrography product that corrects multiple errors from previous DEM-based hydrography maps by removing vegetation bias and improving flow direction accuracy.

2.5.1. Flow Accumulation

Flow accumulation was selected as a key parameter due to its direct relationship with surface runoff concentration and flood generation processes [42]. The raw flow accumulation data (Figure 6) exhibited a highly skewed distribution characteristic of drainage networks and, therefore, a logarithmic transformation was applied:

$$Flow_{log} = \log_{10}(FlowAccumulation + 1) \quad (2)$$

This transformation normalizes the distribution and enhances the discriminative power of the factor in subsequent analysis [43].

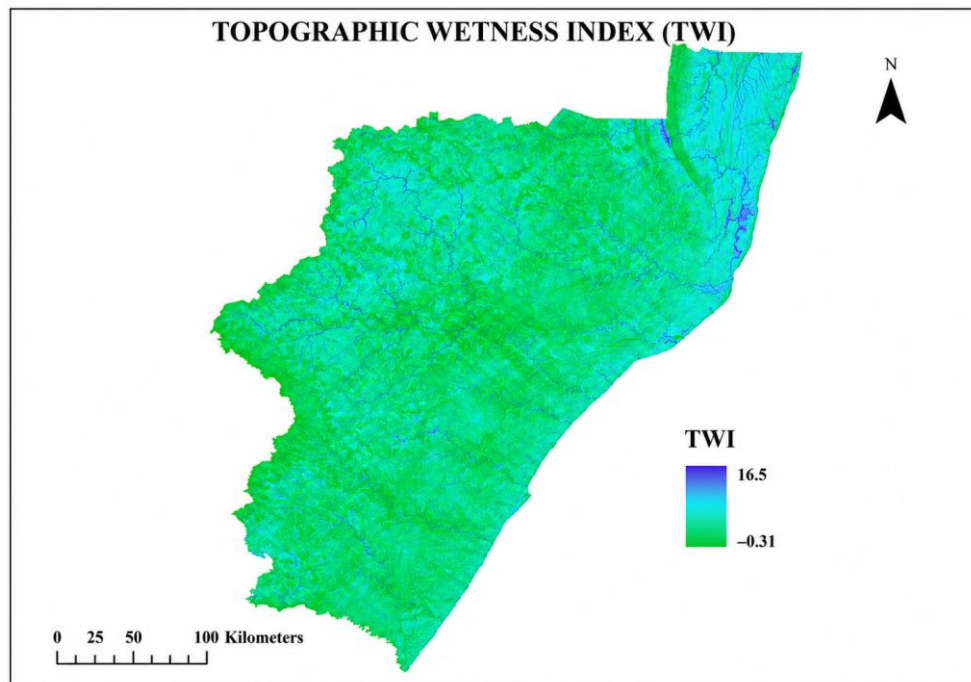


Figure 5. Topographic wetness index (TWI) map of KwaZulu-Natal.

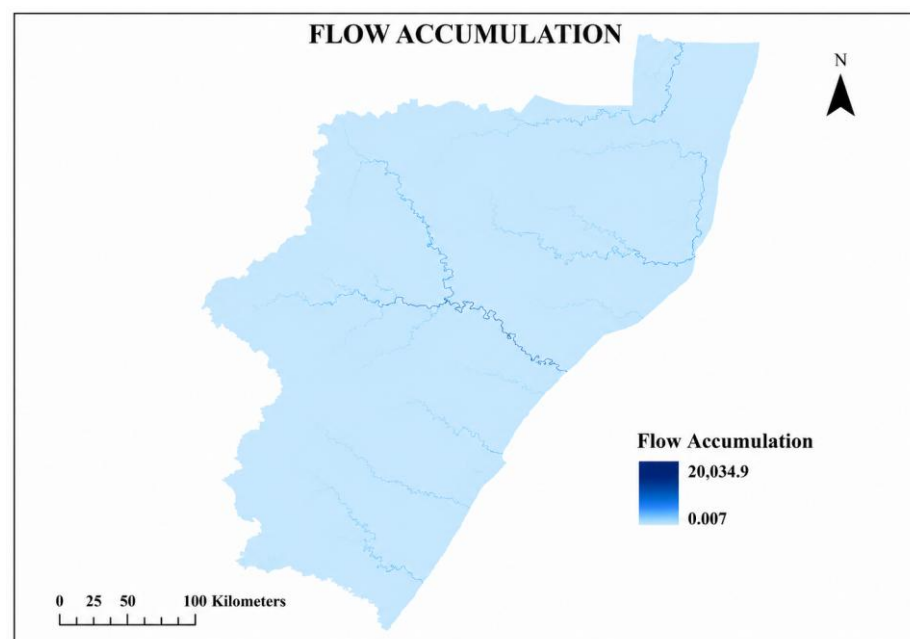


Figure 6. Flow accumulation map of KwaZulu-Natal.

2.5.2. Distance to River Network

Proximity to river networks is a critical hydrological factor, as areas closer to rivers are more susceptible to flooding during high precipitation events or when river levels rise rapidly [44]. A river network was extracted from flow accumulation data by applying a threshold of 50 km² upstream area, which identified significant watercourses based on regional drainage characteristics. Euclidean distance to this network (Figure 7) was calculated using a fast distance transform algorithm:

$$\text{Dist}_{\text{river}} = \sqrt{\text{DTFT}(\text{riverMask})} \quad (3)$$

where DTFT represents the Distance Transform Fast algorithm, which efficiently computes distances across the raster domain [45].

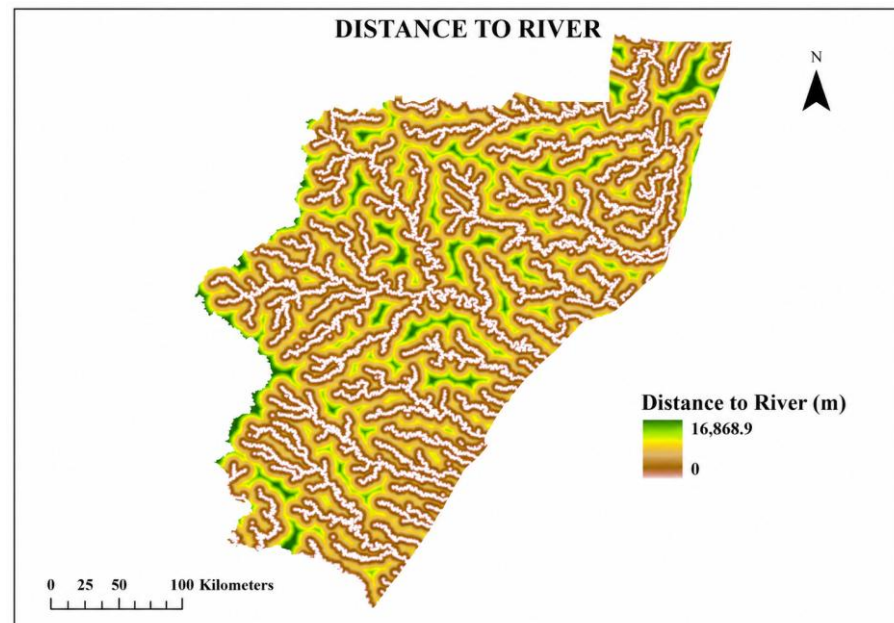


Figure 7. Distance to river map of KwaZulu-Natal.

2.5.3. Drainage Density Proxy

Drainage density, defined as the total length of stream channels per unit area, influences flood susceptibility through its effect on runoff efficiency and basin response time [46]. A drainage density proxy (Figure 8) was generated by applying a 10-pixel (approximately 2.5 km) square kernel mean filter to the river mask:

This approach provides a continuous representation of drainage network concentration.

$$\text{Drainage Density} = \text{riverMask}_{10 \times 10 \text{ kernel}} \quad (4)$$

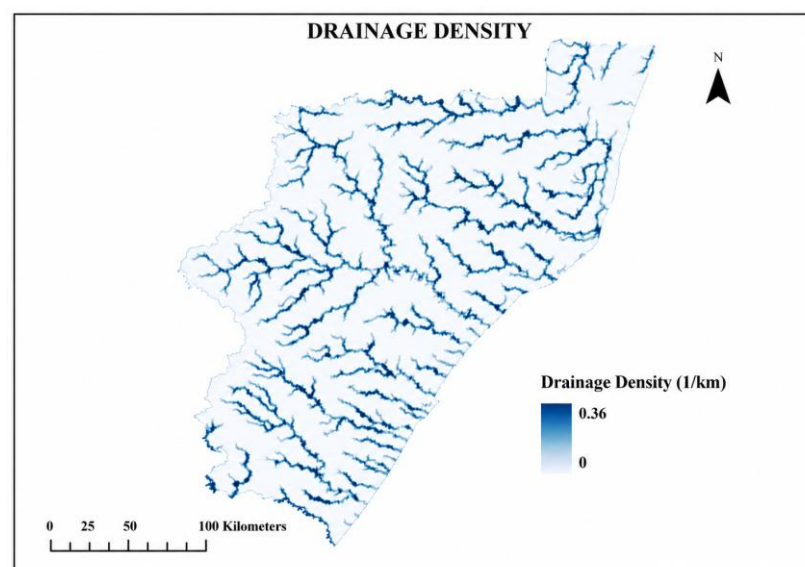


Figure 8. Drainage density map for KwaZulu-Natal.

2.6. Land Use and Land Cover (LULC) Reclassification

Anthropogenic and biophysical influences on flood potential were incorporated through land use and land cover analysis using the South African land use and land cover (LULC) map of 2022 that was reclassified into 8 LULC classes at 20 m resolution as presented in Figure 9.

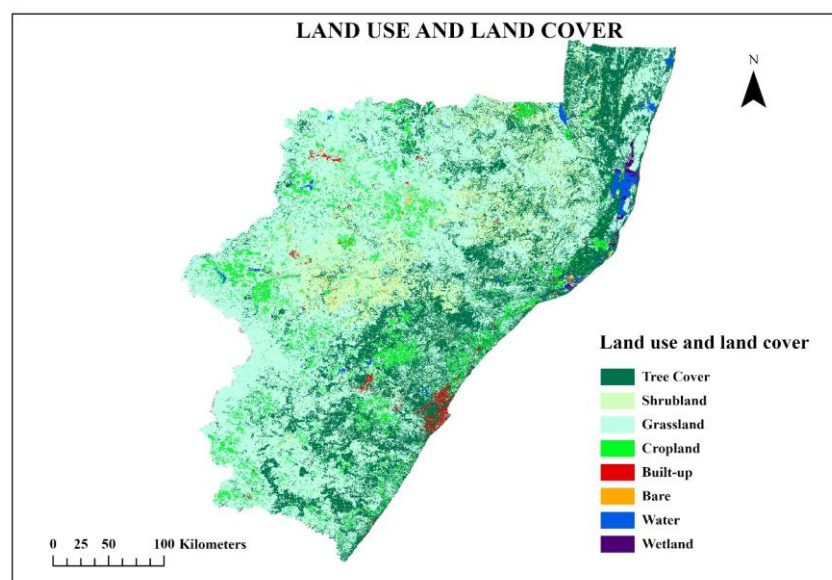


Figure 9. Land use and land cover (LULC) map for KwaZulu-Natal.

The reclassification assigned flood susceptibility scores between 0.1 (lowest susceptibility) and 0.9 (highest susceptibility), as elaborated in Table 2, and the corresponding map is presented in Figure 10 as per [47].

Table 2. Land use/land cover reclassification scheme.

KwaZulu-Natal	Class Code	Flood Susceptibility Value	Hydrological Rationale
Tree cover	10	0.2	High infiltration capacity, canopy interception, high evapotranspiration
Shrubland	20	0.4	Moderate infiltration, seasonal leaf loss
Grassland	30	0.6	Reduced infiltration compared to forests, surface roughness
Cropland	40	0.3	Seasonal vegetation cover, tillage effects on infiltration
Built-up	50	0.9	Impervious surfaces, rapid runoff generation, reduced lag time
Bare	60	0.7	Limited infiltration, surface crusting, minimal interception
Water	80	0.8	Inherently flood-prone areas, no infiltration capacity
Wetland	90	0.5	Saturated conditions, natural flood storage, high infiltration

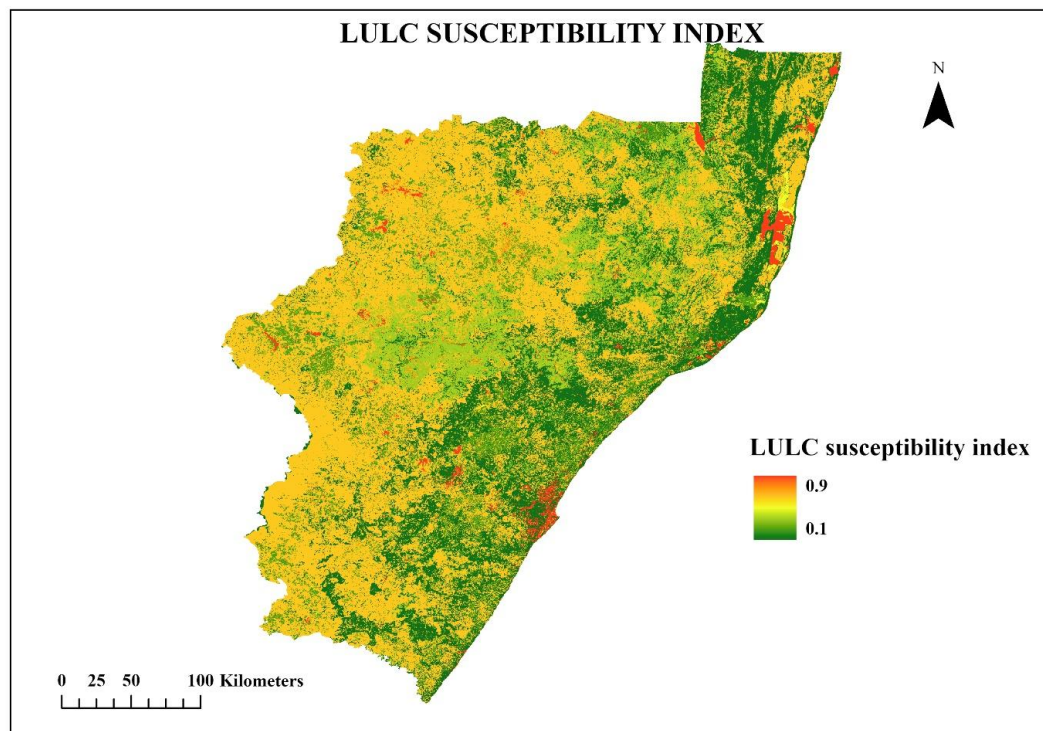


Figure 10. LULC susceptibility index map for KwaZulu-Natal.

2.7. Vegetation Index (NDVI)

Vegetation density and health were characterized using the normalized difference vegetation index derived from Sentinel-2 Harmonized Surface Reflectance imagery:

$$\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} = \frac{\text{B8} - \text{B4}}{\text{B8} + \text{B4}} \quad (5)$$

The Sentinel-2 collection was filtered to the period 2020–2023, with cloud cover below 20%, and reduced to a median composite to minimize atmospheric and seasonal effects. NDVI (Figure 11) correlates inversely with flood susceptibility, as densely vegetated areas typically exhibit higher infiltration rates, greater surface roughness, and increased evapotranspiration [48]. In this study, vegetation conditions were represented using NDVI-derived correction factors; however, the land-cover dataset used in the modelling framework represents a static snapshot of catchment conditions. Consequently, the framework does not explicitly capture ongoing land-cover changes, such as progressive deforestation, urban expansion, or vegetation recovery, which may alter future runoff generation processes. Future applications should incorporate time-varying land-cover datasets or remote sensing-based vegetation monitoring to account for evolving catchment conditions under climate and land-use change scenarios.

2.8. Rainfall Analysis

Climatic influence was integrated using precipitation data from the CHIRPS (Climate Hazards Group InfraRed Precipitation with Station) daily dataset [49]. CHIRPS has been extensively validated for hydrological applications and demonstrates strong performance in capturing extreme rainfall events and deriving flood hazards [50]. A mean annual rainfall layer (Figure 12) was generated by aggregating daily data over a 14-year period (2010–2023):

$$\text{Rainfall}_{\text{mean}} = \frac{1}{n} \sum_{i=2010}^{2023} \sum_{j=1}^{365} \text{Rainfall}_{i,j} \quad (6)$$

This long-term average captures the spatial gradient of precipitation across KwaZulu-Natal, from approximately 600 mm in rain-shadow areas to over 1600 mm in coastal and escarpment regions.

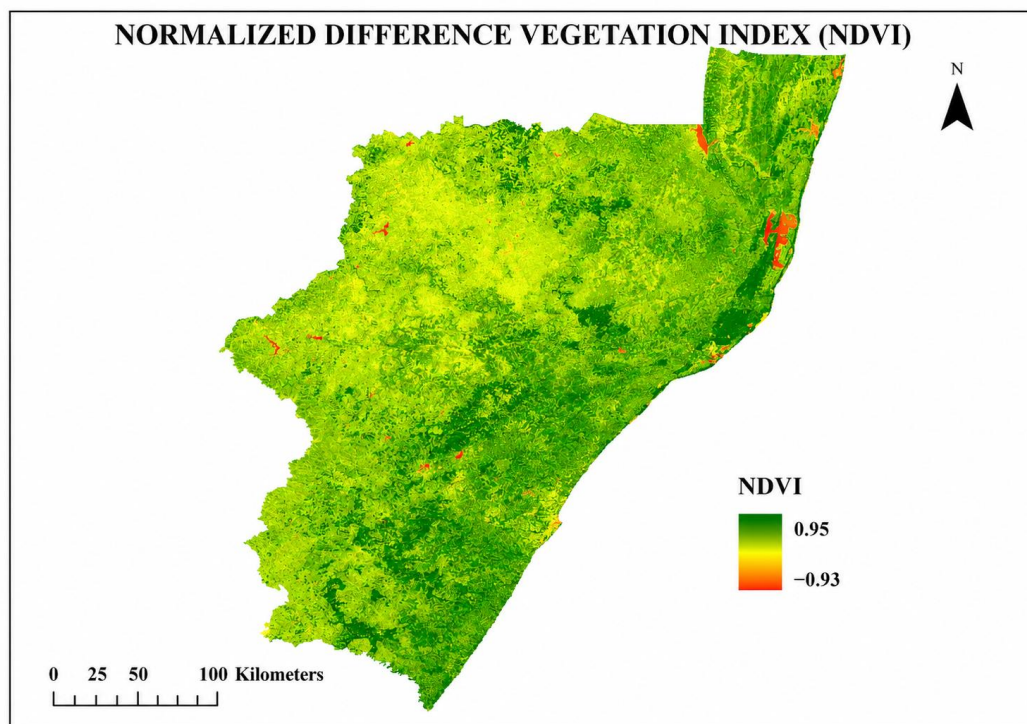


Figure 11. NDVI map for KwaZulu-Natal.

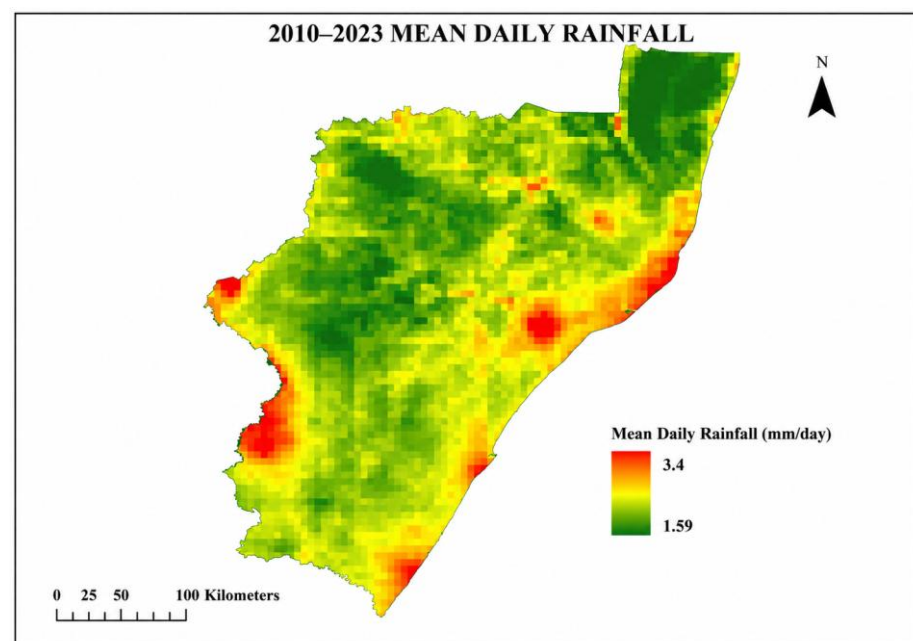


Figure 12. 2010–2023 mean daily rainfall for KwaZulu-Natal.

2.9. Soil and Lithology Proxies

Due to the absence of detailed soil and geological maps at a consistent spatial resolution, proxy layers were derived from slope characteristics following established geomorphological principles.

2.9.1. Soil Proxy

Soil development and depth generally correlate inversely with slope gradient, as steep slopes promote erosion and limit soil formation [51]. A soil proxy (Figure 13) was generated using unit scaling of slope (0–30° range), with higher values representing deeper, more developed soils.

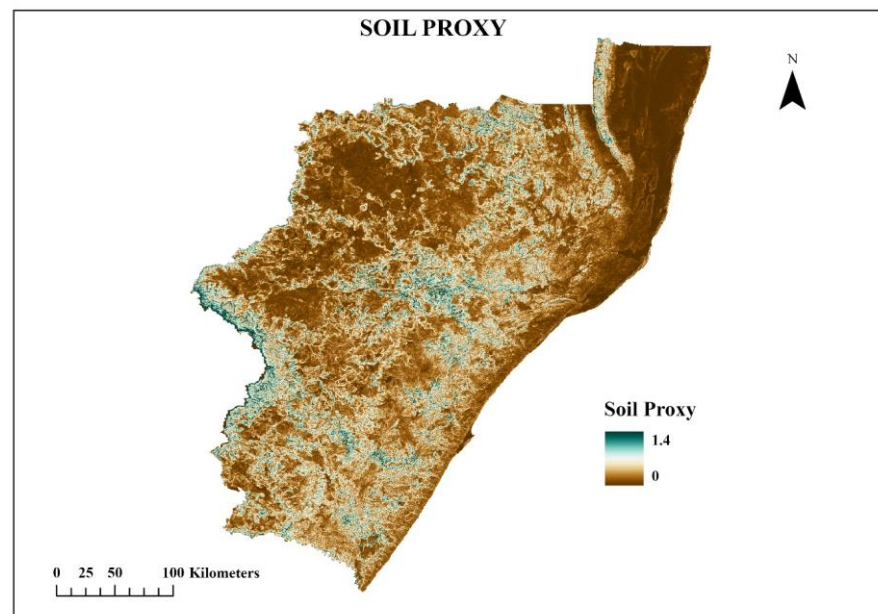


Figure 13. Soil proxy map for KwaZulu-Natal.

2.9.2. Lithology Proxy

Lithological influence on permeability and structural controls was similarly represented through slope characteristics, with the same unit scaling applied (Figure 14). Both proxies were subsequently inverted ($1 - \text{normalized value}$) to align with flood susceptibility logic, where flatter areas with deeper soils (higher proxy values) were assigned higher susceptibility due to reduced runoff potential [6].

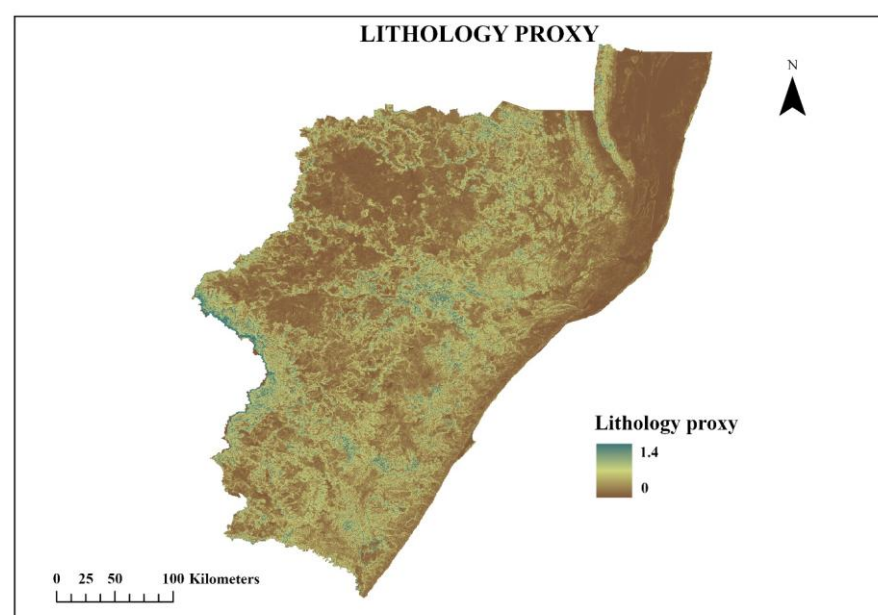


Figure 14. Lithology proxy map for KwaZulu-Natal.

2.10. Normalization and Standardization

All factor layers in Table 3 were normalized to a consistent 0–1 range using a percentile-based approach that minimizes the influence of outliers:

$$X_{\text{norm}} = \frac{X - P_2}{P_{98} - P_2} \quad (7)$$

where P_2 and P_{98} represent the 2nd and 98th percentiles of the factor distribution within the study area. Values were clamped to the (0, 1) interval following transformation. This approach preserves the relative distribution while ensuring all factors contribute equitably to the composite index [52,53]. For factors with inverse relationships to flood susceptibility (elevation, slope, distance to river, NDVI, soil proxy, lithology proxy), a subsequent inversion was applied:

$$X_{\text{norm_inverted}} = 1 - X_{\text{norm}} \quad (8)$$

Table 3. Factor normalization parameters.

Factor	Normalization Range	Inversion Applied	Relationship to Susceptibility
Elevation	2nd-98th percentile	Yes	Inverse (higher elevation = lower susceptibility)
Slope	2nd-98th percentile	Yes	Inverse (steeper = lower susceptibility)
Curvature	2nd-98th percentile	No	Direct (concave = higher susceptibility)
TWI	2nd-98th percentile	No	Direct (higher TWI = higher susceptibility)
Flow Accumulation (log)	2nd-98th percentile	No	Direct (higher accumulation = higher susceptibility)
Distance to River	2nd-98th percentile	Yes	Inverse (closer = higher susceptibility)
Drainage Density	2nd-98th percentile	No	Direct (higher density = higher susceptibility)
LULC Susceptibility	2nd-98th percentile	No	Direct (higher score = higher susceptibility)
NDVI	2nd-98th percentile	Yes	Inverse (denser vegetation = lower susceptibility)
Rainfall	2nd-98th percentile	No	Direct (higher rainfall = higher susceptibility)
Soil Proxy	2nd-98th percentile	Yes	Inverse (steeper slopes = shallower soils = lower susceptibility)
Lithology Proxy	2nd-98th percentile	Yes	Inverse (steeper slopes = exposed rock = lower susceptibility)

All conditioning factors were normalized to a common range of 0–1 using percentile-based min–max normalization based on the 2nd (P_2) and 98th (P_{98}) percentiles rather than the absolute minimum and maximum values. This approach reduces the influence of extreme outliers while preserving the overall distribution of the data. Values below the 2nd percentile were assigned a normalized value of 0, whereas values above the 98th percentile were assigned a value of 1. Values falling between P_2 and P_{98} were linearly rescaled. Consequently, isolated anomalous values resulting from sensor noise, DEM artefacts, or rare extreme observations did not disproportionately influence the normalization process while maintaining the relative differences among the majority of observations

2.11. Analytical Hierarchy Process (AHP) Weight Determination

Factor weights were determined using the AHP, a structured technique for dealing with complex decisions through pairwise comparisons [54]. A pairwise comparison matrix guided by Saaty [55] was constructed based on expert knowledge and literature review, comparing the relative importance of each factor in contributing to flood susceptibility as presented in Table 4.

Table 4. Pairwise comparison matrix for AHP weight.

Factor	Elev	Slope	TWI	Curv	Flow	River	DD	Soil	Lith	LULC	NDVI	Rain
Elevation	1	2	3	5	2	3	4	4	5	3	5	4
Slope	1/2	1	2	4	1	2	3	3	4	2	4	3
TWI	1/3	1/2	1	4	1	1	2	2	3	2	3	2
Curvature	1/5	1/4	1/4	1	1/4	1/3	1/3	1/2	1	1/3	1	1/2
Flow	1/2	1	1	4	1	2	3	3	4	2	4	3
River	1/3	1/2	1	3	1/2	1	2	2	3	2	3	2
DD	1/4	1/3	1/2	3	1/3	1/2	1	1	2	1	2	1
Soil	1/4	1/3	1/2	2	1/3	1/2	1	1	2	1	2	1
Lith	1/5	1/4	1/3	1	1/4	1/3	1/2	1/2	1	1/2	1	1/2
LULC	1/3	1/2	1/2	3	1/2	1/2	1	1	2	1	2	1
NDVI	1/5	1/4	1/3	1	1/4	1/3	1/2	1/2	1	1/2	1	1/2
Rain	1/4	1/3	1/2	2	1/3	1/2	1	1	2	1	2	1

The ordering of factors within Table 4 follows a thematic grouping (topographic, hydrological, soil, land cover, and climatic variables) for presentation purposes only and did not influence the AHP calculations. In the AHP framework, factor weights are derived from the principal eigenvector of the pairwise comparison matrix, meaning that rearranging the order of rows and columns does not alter the resulting weights provided that the pairwise judgments remain unchanged. The higher weights assigned to topographic variables therefore emerged from the comparative assessments and reflect their widely recognized role in controlling runoff generation, flow concentration, and floodplain inundation, rather than any a priori ranking of the factors.

The principal eigenvector of this matrix in Table 5 yielded the following weight set, with a consistency ratio of 0.03, which was well below the 0.10 threshold, indicating acceptable consistency. Although the consistency ratio (CR = 0.03) indicates that the pairwise comparisons are logically consistent according to the criterion proposed by Saaty [54,55], it does not eliminate the inherent subjectivity associated with expert-based weight assignment. The AHP relies on expert judgement to quantify the relative importance of conditioning factors, and consequently, the resulting weights may vary depending on the knowledge, experience, and perspectives of the decision-makers [56]. This subjectivity is widely recognized as one of the principal limitations of AHP in environmental decision-making and hazard susceptibility mapping [57]. To minimize this limitation, the pairwise comparisons in this study were informed by established hydrological literature and evaluated using the consistency ratio, ensuring that the weighting scheme was both scientifically justified and mathematically coherent.

Table 5. AHP-derived factor weights.

Thematic Category	Factor	Weight	Weight (%)
Topography	Elevation	0.15	15
Topography	Slope	0.12	12
Topography	TWI	0.10	10

Topography	Curvature	0.03	3
Hydrology	Flow Accumulation	0.12	12
Hydrology	Distance to River	0.10	10
Hydrology	Drainage Density	0.08	8
Soil/Lithology	Soil Proxy	0.07	7
Soil/Lithology	Lithology Proxy	0.05	5
Land Cover	LULC	0.08	8
Land Cover	NDVI	0.04	4
Climate	Rainfall	0.06	6
Total		1.00	100

2.12. Ensemble Modelling Approach

To reduce model-specific bias and improve prediction robustness, three distinct susceptibility models were implemented and combined into an ensemble. The selection of three distinct modelling approaches: Analytical Hierarchy Process (AHP), fuzzy logic transformation, and frequency ratio (FR), was motivated by their complementary methodological strengths and the need to address different sources of uncertainty in flood susceptibility assessment. AHP provides a structured framework for incorporating expert hydrological knowledge through pairwise comparisons of conditioning factors [54], yet it remains inherently subjective. Fuzzy logic extends AHP by accommodating gradual transitions between susceptibility classes, better representing the continuous nature of hydrological processes [57,58]. In contrast, FR offers a purely data-driven, probabilistic approach based on empirical flood occurrence relationships, thereby minimizing subjective bias [59].

2.12.1. Flood Susceptibility Index—AHP-Based Model (FSIAHP)

In FSI_{AHP} model, the weighted linear combination of all normalized factors was carried out using AHP-derived weights as per Saaty [54]:

$$FSI_{AHP} = \sum_{i=1}^{12} w_i \times F_{i,norm} \quad (9)$$

where w_i represents the AHP weight for factor i , and $F_{i,norm}$ is the normalized factor layer.

2.12.2. Flood Susceptibility Index—Fuzzy Logic Model (FSI_{Fuzzy})

The flood susceptibility index based on fuzzy logic (FSI_{Fuzzy}) was developed using a fuzzy set-based GIS overlay approach to explicitly account for the gradual transitions and inherent uncertainty associated with flood conditioning factors [58,60]. Unlike Boolean classification, fuzzy set theory allows each spatial location to possess a degree of membership ranging from 0 (no susceptibility) to 1 (complete susceptibility), thereby providing a more realistic representation of environmental processes [61]. Ten flood conditioning factors were incorporated into the fuzzy model: elevation, slope, topographic wetness index (TWI), curvature, flow accumulation, distance to rivers, drainage density, land use/land cover (LULC), normalized difference vegetation index (NDVI), and mean annual rainfall. Soil and lithology were excluded from the fuzzy implementation because suitable regional datasets with consistent spatial resolution were unavailable, and the use of terrain-derived proxies would have duplicated the influence of slope within the overlay analysis.

Each conditioning factor was transformed into a fuzzy membership layer using linear membership functions with explicitly defined lower and upper control points derived from published flood susceptibility literature and adapted to the physiographic characteristics of KwaZulu-Natal. Increasing linear membership functions were applied to variables exhibiting a positive relationship with flood susceptibility (rainfall, TWI, flow

accumulation, and drainage density), whereas decreasing linear membership functions were assigned to variables exhibiting an inverse relationship with flooding (e.g., elevation, slope, distance to rivers, and NDVI). Land use classes were converted directly into fuzzy membership values based on their relative influence on runoff generation and infiltration capacity [62–64].

The increasing linear fuzzy membership function was defined as:

$$\mu(x) = \begin{cases} 0, & x \leq a, \\ \frac{x-a}{b-a}, & a < x < b, \\ 1, & x \geq b, \end{cases} \quad (10)$$

where a and b are the lower and upper control points, respectively.

For variables exhibiting an inverse relationship with flood susceptibility, the decreasing linear fuzzy membership function is expressed as:

$$\mu(x) = \begin{cases} 1, & x \leq a, \\ \frac{b-x}{b-a}, & a < x < b, \\ 0, & x \geq b. \end{cases} \quad (11)$$

where a and b represent the lower and upper control points defining the transition between minimum and maximum membership values. Control points for each conditioning factor were selected based on published flood susceptibility studies and adapted to the range and characteristics of the corresponding variable within the KwaZulu-Natal study area. Increasing or decreasing linear membership functions were assigned according to the expected relationship between each factor and flood susceptibility. The selected membership functions and associated control points are summarized in Table 6 [39,40,63–66].

Table 6. The selected membership functions and associated control points [39,40,63–66].

Factor	Membership Type	Lower Control Point (a)	Upper Control Point (b)	Relationship
Elevation	Linear decreasing	0 m	1000 m	Lower elevation → higher susceptibility
Slope	Linear decreasing	0°	30°	Gentler slopes → higher susceptibility
Distance to rivers	Linear decreasing	0 m	1000 m	Shorter distance → higher susceptibility
Flow accumulation	Linear increasing	N/A	N/A	Higher accumulation → higher susceptibility
TWI	Linear increasing	3	15	Higher TWI → higher susceptibility
Curvature	Linear	−5	+5	Concave terrain → higher susceptibility
Drainage density	Linear increasing	0	0.5	Higher density → higher susceptibility
NDVI	Linear decreasing	−0.2	0.8	Lower vegetation cover → higher susceptibility
Rainfall	Linear increasing	1	8 mm day ^{−1}	Higher rainfall → higher susceptibility
LULC	Expert membership	Literature-based	Literature-based	Class-specific susceptibility

Following fuzzification, the individual membership layers were integrated using the fuzzy algebraic product and fuzzy algebraic sum operators. The fuzzy algebraic product represents the fuzzy logical AND operator and identifies locations where all conditioning factors simultaneously indicate a high degree of flood susceptibility. It is expressed as;

$$\mu_{\text{product}} = \prod_{i=1}^n \mu_i \quad (12)$$

where μ_i is the fuzzy membership value of the i^{th} flood conditioning factor, and n is the total number of factors included in the analysis.

In contrast, the fuzzy algebraic sum represents the fuzzy logical OR operator and identifies locations where one or more conditioning factors indicate high flood susceptibility. It is defined as;

$$\mu_{\text{sum}} = 1 - \prod_{i=1}^n (1 - \mu_i) \quad (13)$$

The fuzzy algebraic product is generally more restrictive because high output values are obtained only when all input membership values are simultaneously high. Conversely, the fuzzy algebraic sum is more permissive, allowing high susceptibility values when any individual conditioning factor exhibits a high degree of membership. To achieve a balanced integration of these complementary operators, the fuzzy gamma overlay was employed [60,61]. The fuzzy gamma operator combines the algebraic product and algebraic sum according to:

$$\mu_{\gamma} = (\mu_{\text{sum}})^{\gamma} (\mu_{\text{product}})^{(1-\gamma)} \quad (14)$$

where γ is the gamma coefficient ($0 \leq \gamma \leq 1$). Lower gamma values produce results similar to the fuzzy algebraic product (AND), whereas higher values increasingly resemble the fuzzy algebraic sum (OR). In this study, a gamma value of 0.90 was selected to provide an appropriate balance between the restrictive behaviour of the algebraic product and the permissive nature of the algebraic sum while preserving spatial continuity in the flood susceptibility surface [61].

The resulting continuous fuzzy flood susceptibility index (μ_{γ}) ranged from 0 (very low susceptibility) to 1 (very high susceptibility). For interpretation and mapping purposes, the continuous susceptibility surface was subsequently classified into five equal-interval classes: very low (0.0–0.2), low (0.2–0.4), moderate (0.4–0.6), high (0.6–0.8), and very high (0.8–1.0), following approaches commonly adopted in flood susceptibility mapping studies [67,68]. The resulting $\text{FSI}_{\text{Fuzzy}}$ was subsequently integrated with the AHP and frequency ratio models within a multi-model ensemble framework to reduce model-specific biases.

2.12.3. Flood Susceptibility Index—Frequency Ratio-Based Model (FSI_{FR})

In FSI_{FR} model, a simplified model emphasizing hydrological controls was constructed.

$$\text{FSI}_{\text{FR}} = 0.2 \times \text{Flow}_{\text{Norm}} + 0.2 \times \text{River}_{\text{Norm}} + 0.15 \times \text{TWI}_{\text{Norm}} + 0.1 \times \text{Elev}_{\text{Norm}} + 0.15 \times \text{Rain}_{\text{Norm}} + 0.1 \times \text{LULC}_{\text{Norm}} + 0.1 \times \text{Slope}_{\text{Norm}} \quad (15)$$

This configuration reflects the frequency ratio principle, where weights approximate the relative frequency of flood occurrence in each factor class [59].

2.12.4. Flood Susceptibility Index—Ensemble Model ($\text{FSI}_{\text{Ensemble}}$)

The final ensemble susceptibility map was generated as the mean of the three individual models:

$$\text{FSI}_{\text{Ensemble}} = \frac{\text{FSI}_{\text{AHP}} + \text{FSI}_{\text{Fuzzy}} + \text{FSI}_{\text{FR}}}{3} \quad (16)$$

Ensemble approaches have been demonstrated to reduce overfitting, minimize model-specific biases, and improve overall prediction accuracy in natural hazard susceptibility mapping [34,69].

2.13. Model Uncertainty Assessment

To quantify spatial uncertainty arising from inter-model variability, a pixel-wise standard deviation was calculated across the three individual models:

$$\text{Uncertainty} = \sqrt{\frac{\sum_{m=1}^3 (\text{FSI}_m - \text{FSI}_{\text{Ensemble}})^2}{3}} \quad (17)$$

This uncertainty map identifies areas where model agreement is low, indicating regions requiring additional data collection or more sophisticated modelling approaches [70].

2.14. Susceptibility Classification

To enhance interpretability and support decision-making, the continuous ensemble susceptibility index was reclassified into five discrete classes based on natural breaks in the data distribution as presented in Table 7.

Table 7. Flood susceptibility classification scheme.

Class	FSI Range	Susceptibility Level	Areal Extent (Expected)
1	≤0.2	Very Low	~15–20%
2	>0.2–0.4	Low	~25–30%
3	>0.4–0.5	Moderate	~30–35%
4	>0.5–0.8	High	~15–20%
5	>0.8	Very High	~5–10%

This five-class system provides an intuitive framework for communicating flood risk to planners and stakeholders, following conventional cartographic practices for hazard mapping [34]. Export tasks were configured to maximize pixel count limits (1×10^{13}) ensuring complete coverage of the study area at selected resolutions.

2.15. Model Validation Using a Historical Flood Occurrence Inventory

Model validation was undertaken using an independent historical flood occurrence inventory compiled for KwaZulu-Natal covering the period 2015–2025. In the absence of a comprehensive georeferenced provincial flood database, a systematic document-based inventory approach was adopted, consistent with susceptibility validation practices in data-scarce hydrological environments [34,69]. The validation strategy evaluates predictive performance through spatial correspondence between historically documented flood locations and modelled susceptibility classes. Given the recurrence of high-impact flood events in KwaZulu-Natal, including the April 2022 floods contextualized within a long-term provincial chronology by [5,32], the province provides a robust empirical basis for event-based validation.

A structured review of peer-reviewed literature, provincial and municipal disaster management reports, hydro-meteorological assessments, and verified national news archives was conducted to extract flood-affected locations within KZN during the 10-year validation window. Events were retained only if (i) they occurred within the provincial boundary, (ii) the affected locality was spatially identifiable, and (iii) the event date fell within the defined period. For each validated location, geographic coordinates and administrative district information were recorded. Each location was treated as a single confirmed flood occurrence point, thereby generating a binary validation dataset (flood presence). All validated locations were geocoded and converted into a spatial point dataset to produce the Historical Flood Occurrence Layer (HFOL). The HFOL was subsequently overlaid with the classified ensemble flood susceptibility map.

2.15.1. High-Susceptibility Capture Rate (HSCR)

Model predictive performance was primarily evaluated using the High-Susceptibility Capture Rate (HSCR), defined as the proportion of historical flood locations captured within the High and Very High susceptibility classes:

$$HSCR = \frac{N_H + N_{VH}}{N_{total}} \times 100 \quad (18)$$

The HSCR quantifies the model's ability to correctly classify historically flood-affected areas as highly susceptible. Higher values indicate stronger agreement between modelled hydro-geomorphological predisposition and observed flood occurrence. Model performance was interpreted according to the magnitude of HSCR and the class-specific proportional distribution. An HSCR exceeding approximately 70% was considered indicative of strong predictive performance, consistent with established thresholds in flood susceptibility validation studies.

2.15.2. Receiver Operating Characteristic (ROC) and Area Under Curve (AUC) Validation

To complement the High-Susceptibility Capture Rate (HSCR) and provide a more rigorous quantitative assessment of model discriminative ability, Receiver Operating Characteristic (ROC) curve analysis was conducted. The ROC curve is a fundamental tool for evaluating binary classification performance, plotting the true positive rate (sensitivity) against the false positive rate (1 – specificity) across all possible susceptibility thresholds [71]. The Area Under the ROC Curve (AUC) quantifies the overall predictive performance of the ensemble model, with values ranging from 0.5 (random classification) to 1.0 (perfect discrimination). AUC values above 0.8 are generally interpreted as indicating good model performance, while values above 0.9 indicate excellent discriminative ability [72]. The ROC analysis was implemented using the pROC package in R [73], with 95% confidence intervals calculated through 2000 bootstrap replicates.

2.15.3. Confusion Matrix-Based Performance Assessment

To provide an additional quantitative evaluation of predictive performance, confusion matrix analysis was conducted for each susceptibility model (AHP, fuzzy logic, frequency ratio, and Ensemble). Historical flood locations were treated as positive observations, while randomly generated points distributed across the study area represented pseudo-absence locations. Continuous susceptibility values were converted into binary predictions using a threshold value of 0.50, whereby values ≥ 0.50 were classified as flood-susceptible and values < 0.50 as non-susceptible. The resulting confusion matrices were used to calculate true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN), from which accuracy, precision, recall (sensitivity), specificity, and F1-score were computed according to the following equations:

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (19)$$

Precision

$$Precision = \frac{TP}{TP + FP} \quad (20)$$

Recall

$$Recall = \frac{TP}{TP + FN} \quad (21)$$

Specificity

$$Specificity = \frac{TN}{TN + FP} \quad (22)$$

F1-score

$$F1 = \frac{2TP}{2TP + FP + FN} \quad (23)$$

Figure 15 presents a graphical summary of the methodological framework adopted in this study. The workflow illustrates the sequential implementation of the ensemble

flood susceptibility modelling approach, beginning with data acquisition and preprocessing within the Google Earth Engine platform, followed by derivation and normalization of flood conditioning factors, development of the AHP, fuzzy logic, and frequency ratio models, ensemble integration, spatial uncertainty assessment, susceptibility classification, and model validation using historical flood occurrences. The flowchart provides an overview of the complete analytical workflow and the interrelationships between the individual modelling components.

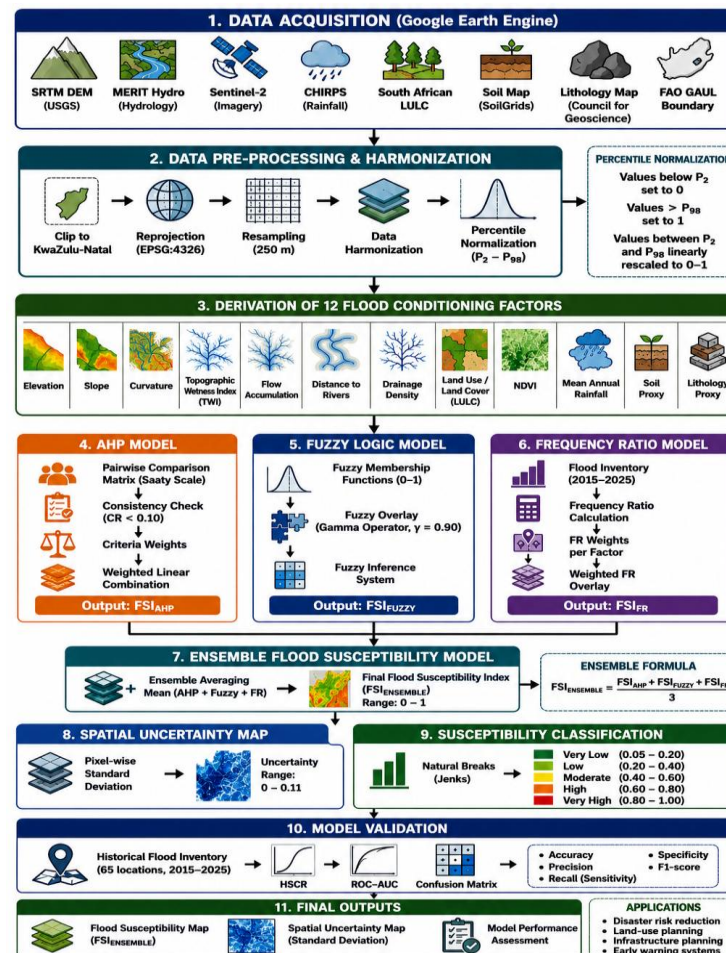


Figure 15. Graphical summary of the methodological framework adopted for ensemble flood susceptibility mapping in KwaZulu-Natal.

3. Results and Discussion

3.1. Comparative Analysis of Flood Susceptibility Index (FSI) Distributions and Ensemble Model Performance

The Analytic Hierarchy Process (AHP) model produced FSI values ranging from 0.03 to 0.97, indicating moderate dispersion across the susceptibility continuum (Figure 16). The distribution reflects structured weighting of conditioning factors through pairwise comparison matrices. While the lower bound close to zero suggests the model effectively distinguishes low-risk terrain, the upper bound approaching unity confirms identification of highly flood-prone zones. However, the AHP framework remains sensitive to subjective judgement embedded in expert-based weighting [74,75]. Although consistency ratios were maintained within acceptable thresholds, minor variations in weight allocation may influence spatial susceptibility gradients. Nonetheless, the spread observed indicates reasonable differentiation between stable and hazard-prone landscapes.

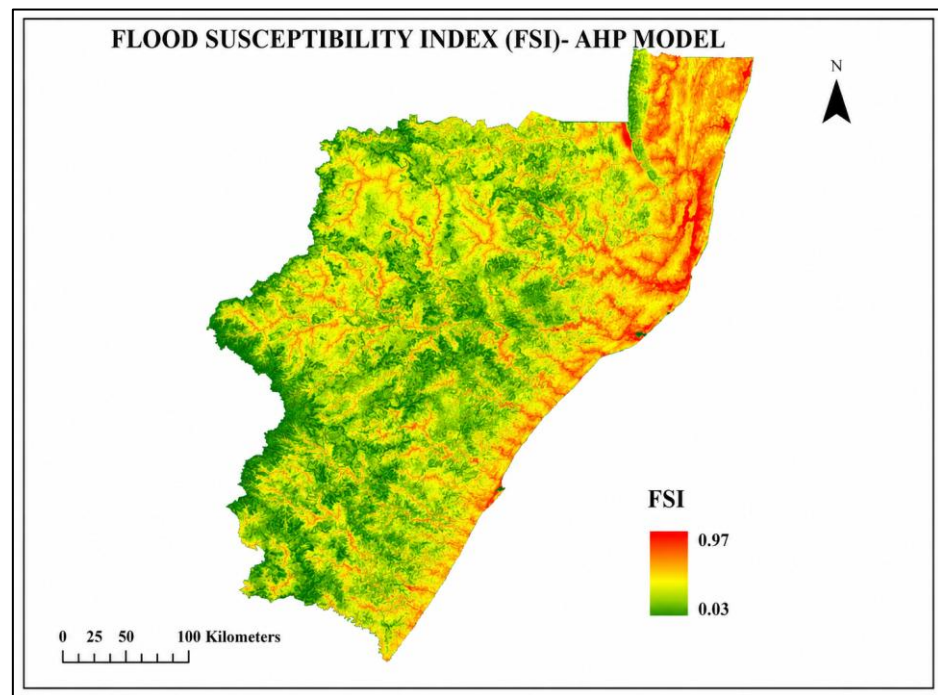


Figure 16. Flood susceptibility index (FSI)—AHP model.

The fuzzy logic model generated FSI values between 0.04 and 0.93 (Figure 17), exhibiting a slightly lower upper-tail concentration compared to AHP. The occurrence of maximum susceptibility values along river networks reflects the ability of fuzzy membership functions to assign high membership values to locations exhibiting combinations of environmental conditions that are most conducive to flooding. In fuzzy set theory, areas with characteristics closely matching predefined flood-prone conditions receive membership values approaching 1, representing a high degree of flood susceptibility rather than a binary classification [58,60]. Unlike AHP's discrete weighting, fuzzy modelling accommodates gradual transitions between susceptibility classes, which aligns more realistically with hydrological processes that operate along a continuum rather than fixed thresholds. The wider upper range suggests enhanced sensitivity to extreme hazard zones, particularly in low-lying areas, high-runoff surfaces, and areas in proximity to river buffers.

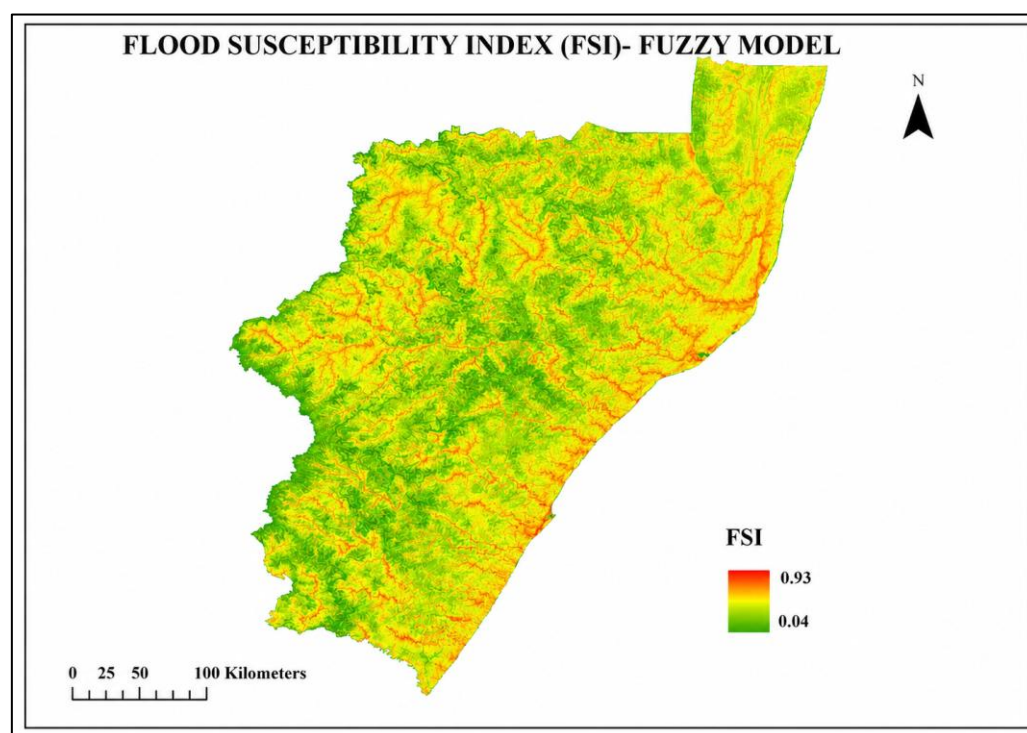


Figure 17. Flood susceptibility index (FSI)—fuzzy model.

The frequency ratio (FR)-based model produced FSI values ranging from 0.06 to 1.00 (Figure 18). The slightly elevated lower bound relative to AHP and fuzzy outputs indicates that the probabilistic weighting scheme inherent in FR reduces extremely low susceptibility assignments. Because FR quantifies the ratio between flood occurrence probability and spatial factor distribution, it emphasizes empirically observed flood conditioning relationships. The upper limit reaching unity demonstrates strong alignment between historical flood locations and high-weight conditioning factors. Compared to the deterministic AHP approach, FR is more data-driven, minimizing subjective bias.

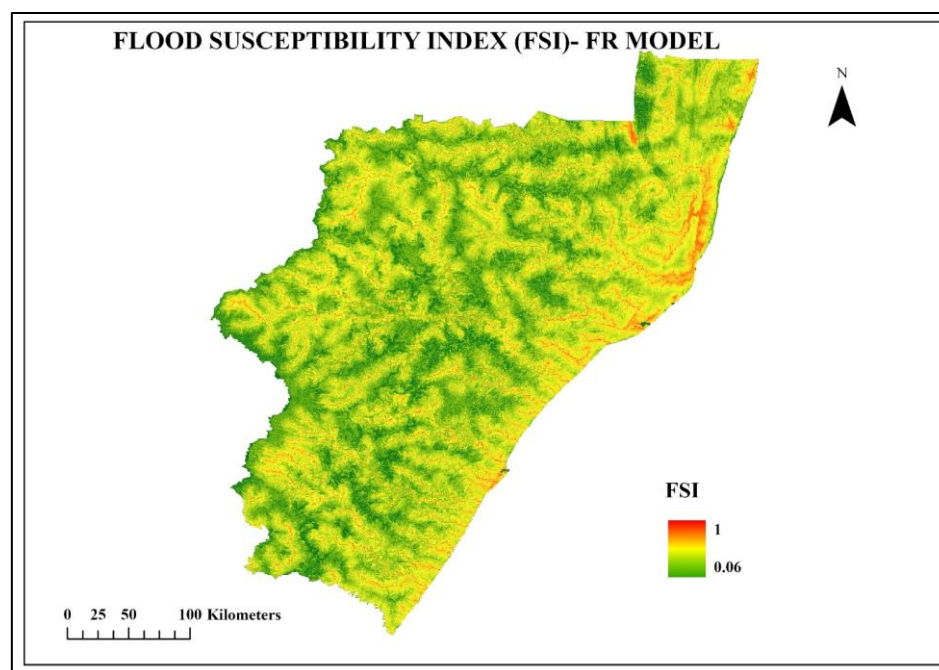


Figure 18. Flood susceptibility index (FSI)—frequency ratio model.

The ensemble model integrated outputs from AHP, fuzzy logic, and FR approaches, producing an FSI range of 0.05 to 1.00 (Figure 19). The distribution indicates a moderate lower-bound response, characteristic of multi-model aggregation where extreme low-risk noise is suppressed and high-risk signals are reinforced. By combining deterministic expert weighting (AHP), nonlinear transition handling (fuzzy logic), and probabilistic evidence-based weighting (FR), the ensemble framework enhances spatial stability. Notably, while the fuzzy model slightly exaggerates extreme susceptibility zones and AHP may reflect subjective bias, the ensemble approach balances these tendencies, reducing both overestimation and underestimation. This moderation effect suggests improved generalization capability and reduced overfitting. Spatially, the ensemble map displays smoother susceptibility gradients, reflecting harmonized terrain–hydrological interactions.

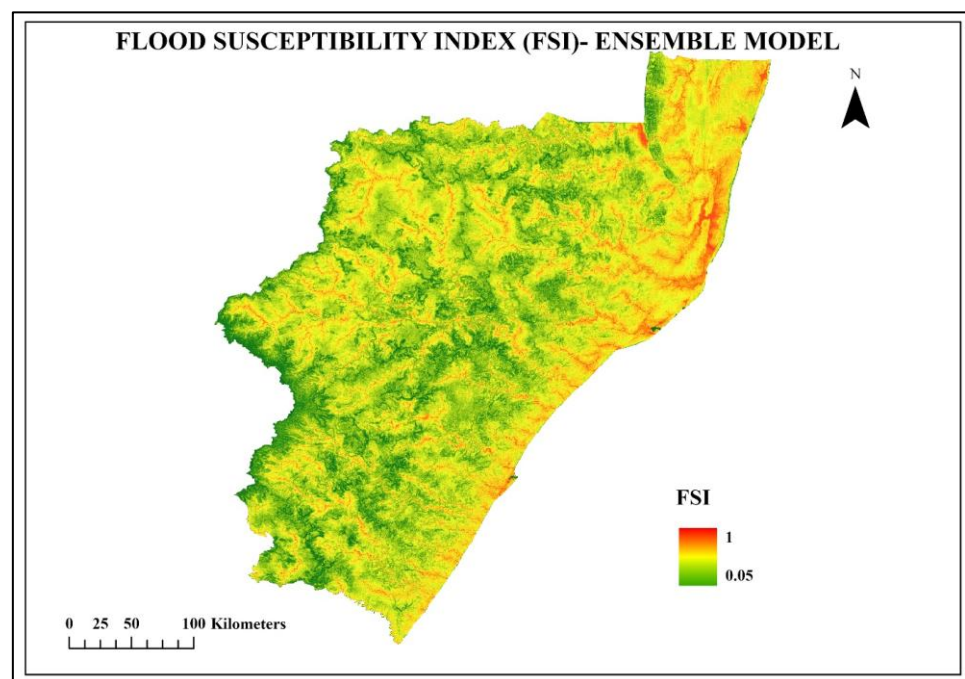


Figure 19. Flood susceptibility index (FSI)—ensemble model.

The uncertainty surface ranged from 0.00 to 0.13 (Figure 20), indicating relatively low predictive ambiguity across the study area. Values approaching zero denote strong agreement among the four modelling approaches, whereas values nearing 0.13 highlight localized areas of classification instability, potentially corresponding to transitional geomorphic zones. Statistically, the narrow uncertainty band suggests robust internal consistency among models. In hydrological susceptibility modelling, uncertainty magnitudes below 0.15 are generally interpreted as acceptable predictive confidence. Therefore, the observed range supports the reliability of the ensemble framework relative to individual models. The uncertainty analysis quantifies the spatial agreement among the three susceptibility models and should therefore be interpreted as a measure of model-consensus uncertainty rather than total predictive uncertainty arising from input data, model structure, or parameter uncertainty.

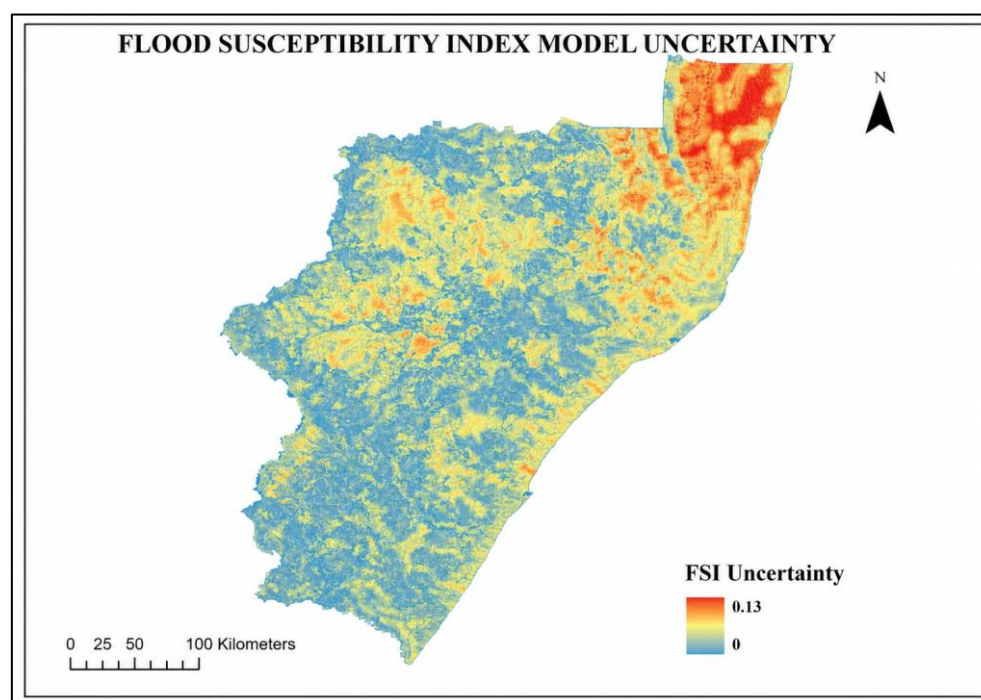


Figure 20. Model uncertainty surface.

Among the four modelling approaches, each method contributed distinct analytical strengths to flood susceptibility assessment. The AHP model provided a structured multi-criteria weighting framework, although it remains partially influenced by expert judgement. The fuzzy logic approach provided susceptibility patterns that were consistent with expected hydrological controls by allowing gradual transitions between susceptibility classes and demonstrated increased sensitivity to extreme hazard zones. In contrast, the frequency ratio model applied empirical, probability-based weighting derived from historical flood occurrences, thereby reducing subjectivity and strengthening data-driven inference. The ensemble model integrated these complementary methodologies and produced the most spatially stable and generalized susceptibility representation. The highest model uncertainty (0.09–0.13) was concentrated in uMkhanyakude District's low-gradient coastal plains, characterized by elevations below 100 m, and slopes below 2°. This is where multiple flood mechanisms including fluvial, pluvial, groundwater, and estuarine co-occur without a single dominant control. This process ambiguity causes the three modelling approaches to diverge, unlike steep escarpments or well-defined river corridors, where unambiguous terrain produces strong model convergence.

The flood susceptibility map (Figure 21) indicates that Very Low susceptibility areas constitute 3.12% of the study area, while Low susceptibility covers 37.43%. The largest proportion of the area falls within the Moderate class (51.08%), indicating that more than half of the landscape exhibits intermediate flood susceptibility conditions. Areas classified as High and Very High account for 7.56% and 0.80%, respectively, collectively representing a relatively small but critical portion of the study area exposed to elevated flood risk. This distribution suggests that although extreme susceptibility zones are spatially limited, a substantial proportion of the region remains moderately prone to flooding, highlighting the need for proactive land-use planning and targeted risk mitigation strategies.

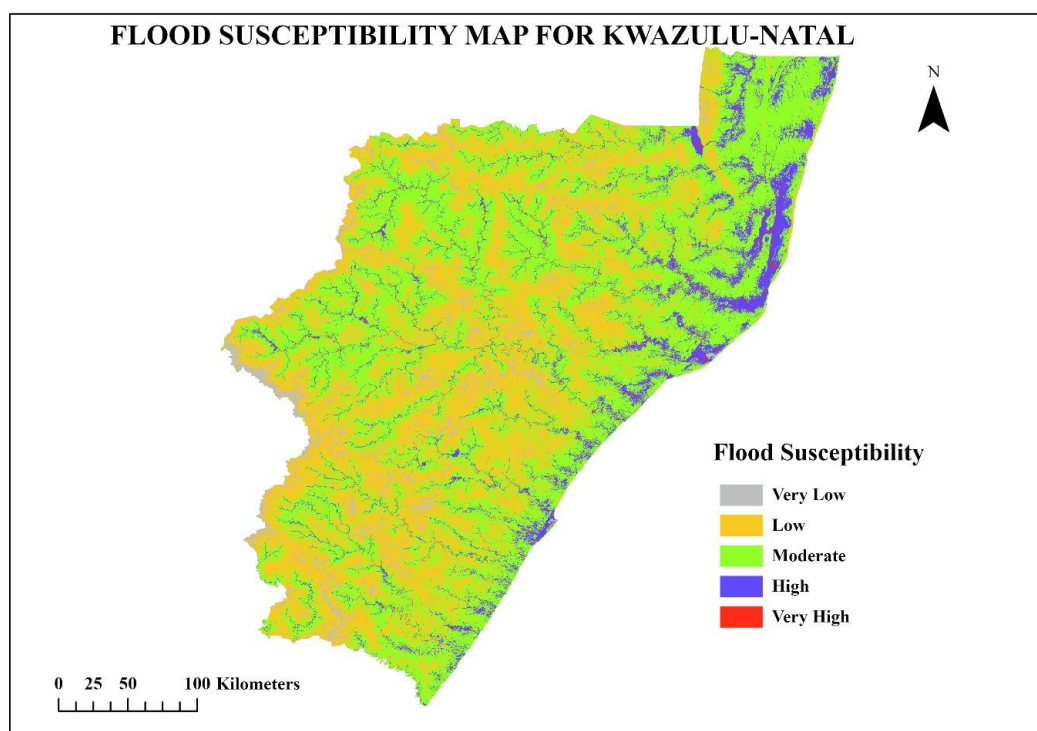


Figure 21. Flood susceptibility classes.

3.2. Spatial Pattern of Flood Susceptibility and Model Reliability

The ensemble flood susceptibility model demonstrated strong spatial discrimination capability, with most historical flood occurrences concentrated within high susceptibility zones. The validation dataset comprised 65 historical flood locations, as presented in Figure 22.

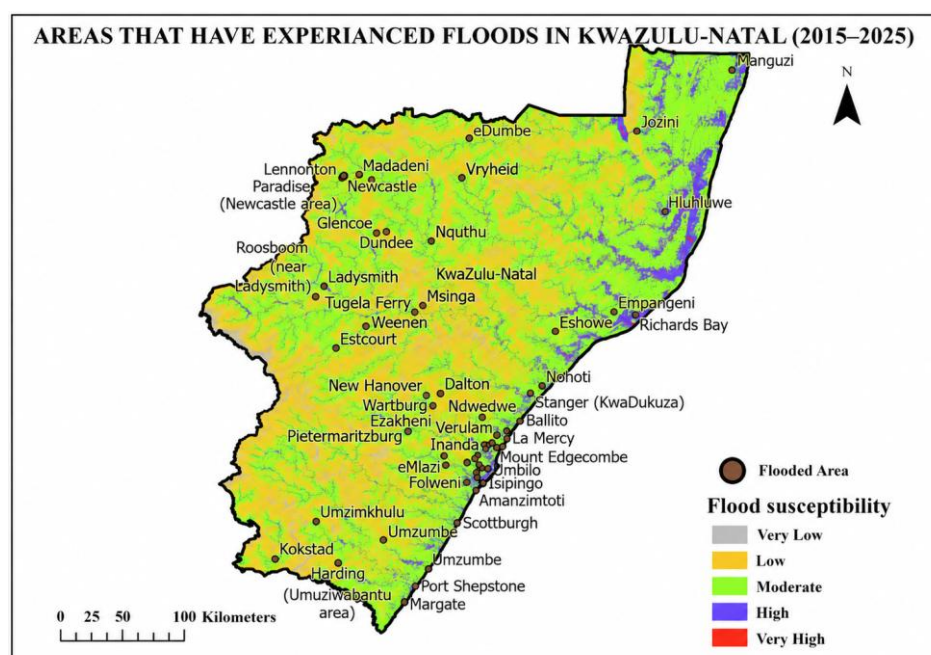


Figure 22. Areas that have been reported to experience floods (2015–2025).

Spatial aggregation of flood-prone locations indicates a pronounced concentration within coastal and urbanized administrative regions. The highest frequency was observed

in eThekweni Metropolitan Municipality, accounting for 26 reported places, reflecting the influence of dense settlement patterns, extensive impervious surfaces, and complex coastal drainage systems. The second highest count occurred in Ugu District Municipality with 6 locations, highlighting vulnerability along the southern coastal corridor. Three districts including Amajuba District Municipality, uThukela District Municipality, and uMzinyathi District Municipality recorded 5 flood-prone places each, indicating moderate inland exposure associated with township settlements and riverine catchments. Overall, the distribution demonstrates strong coastal urban dominance in flood reporting, with susceptibility signals decreasing toward less densely populated inland districts.

The frequency distribution of flooded areas across susceptibility classes is presented in Table 8.

Table 8. Flood point distribution across susceptibility classes.

Susceptibility Level	Frequency	Percentage (%)
Low	5	7.69
Moderate	10	15.38
High	48	73.85
Very High	2	3.08
Total	65	100

The observed 73.85% concentration of flood points within the high susceptibility class indicates strong predictive spatial performance of the ensemble model. This pattern aligns with established flood susceptibility modelling literature, which suggests that successful hazard models should demonstrate substantial clustering of historical flood inventories within high-risk zones without forcing artificial segregation of flood occurrences exclusively into extreme hazard classes [76,77]. Flood susceptibility mapping is fundamentally a probabilistic hazard representation rather than a deterministic event prediction framework [78]. This interpretation is supported by the validation results obtained in this study: while 73.85% of the historical flood locations were correctly classified within the High susceptibility class, 15.38% and 7.69% occurred within the Moderate and Low susceptibility classes, respectively. This distribution indicates that flood occurrence cannot be represented as a purely deterministic process because individual flood events are also influenced by dynamic factors, including rainfall intensity, antecedent soil moisture, drainage capacity, and local anthropogenic modifications, which are not explicitly represented in a static susceptibility model. Consequently, the ensemble model estimates the spatial likelihood of flooding rather than predicting the exact occurrence of individual flood events. The results are consistent with ensemble modelling approaches reported in previous studies, where integration of multiple conditioning factors improves spatial prediction stability and reduces model uncertainty [79–81]. Similar predictive behaviour has been observed in multi-criteria flood hazard assessment conducted in coastal catchments of southern Africa [82].

3.3. Class Distribution and Model Robustness

The distribution of flood points across susceptibility classes demonstrates appropriate gradient transition behaviour, indicating that the model is not overfitted. The presence of 15.38% of flood points in moderate susceptibility zones reflects transitional hydrological response conditions. These zones often represent areas where flood generation mechanisms are influenced by the combined effects of rainfall intensity, land surface permeability, and drainage network connectivity. The small proportion of flood points in very high susceptibility zones (3.08%) is scientifically acceptable. Very high susceptibility zones

typically correspond to hydrogeomorphic features such as river channels or low-lying flood storage areas, where human settlement density may be relatively low.

The ROC curve analysis confirmed the ensemble model's good agreement with the available historical flood inventory, yielding an AUC of 0.852 (95% CI: 0.7952–0.852) (Figure 23). This value indicates that the model has an 85.2% probability of correctly distinguishing a randomly selected flood point from a randomly selected non-flood point.

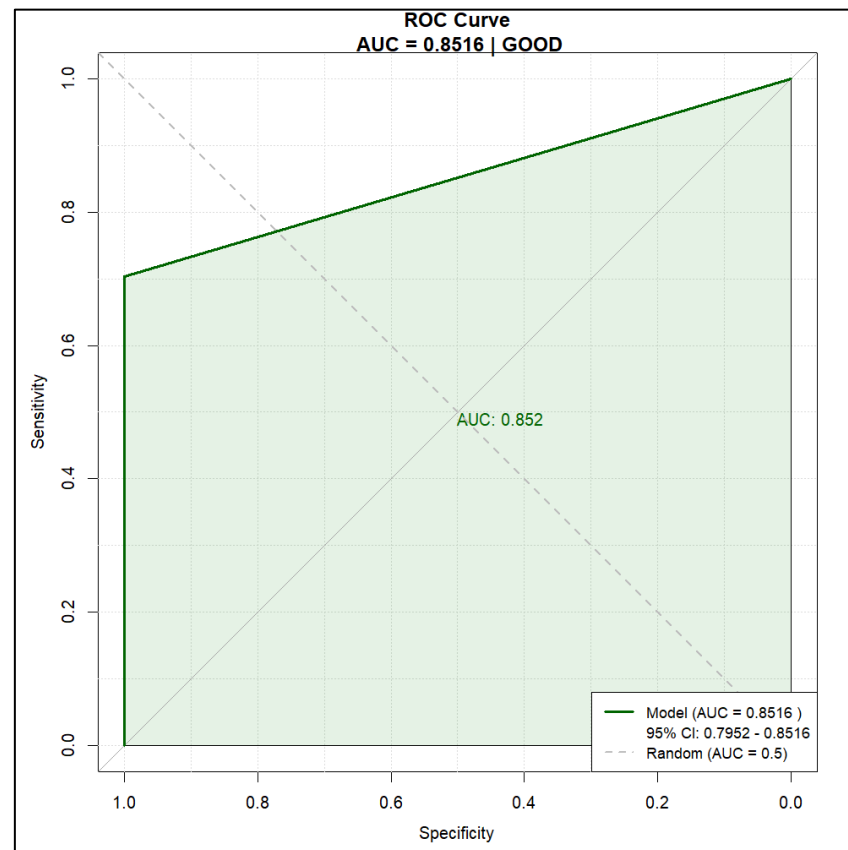


Figure 23. Receiver Operating Characteristic (ROC) curve for the ensemble flood susceptibility model.

The ROC analysis employed a rigorous validation design, comparing all 65 historical flood locations against non-flood reference points. Despite this stringent test, the model achieved good discriminative ability, with the AUC exceeding the conventional threshold for acceptable model performance ($AUC > 0.8$). The 95% confidence interval of 0.7952–0.852 indicates statistical reliability, with the lower bound remaining above 0.8. This narrow uncertainty range reflects the ensemble model's stability and confirms that the observed performance is not an artefact of sampling variability.

The density plot (Figure 24) reveals that flood points are not uniformly distributed across the susceptibility spectrum but rather cluster within the High (0.5–0.8) and Very High (>0.8) classes.

This clustering indicates that the ensemble model successfully captures the hydrogeomorphological conditions that predispose landscapes to flooding, including low elevation, gentle slopes, high TWI, and proximity to drainage networks. The minimal overlap between curves in the 0.2–0.3 range suggests that the model reliably identifies genuinely low-risk areas. However, the partial overlap in the 0.4–0.5 zone reflects the hydrologically realistic uncertainty in classifying transitional landscapes where flood occurrence depends on event-specific factors (rainfall intensity, antecedent moisture) not captured in static susceptibility models.

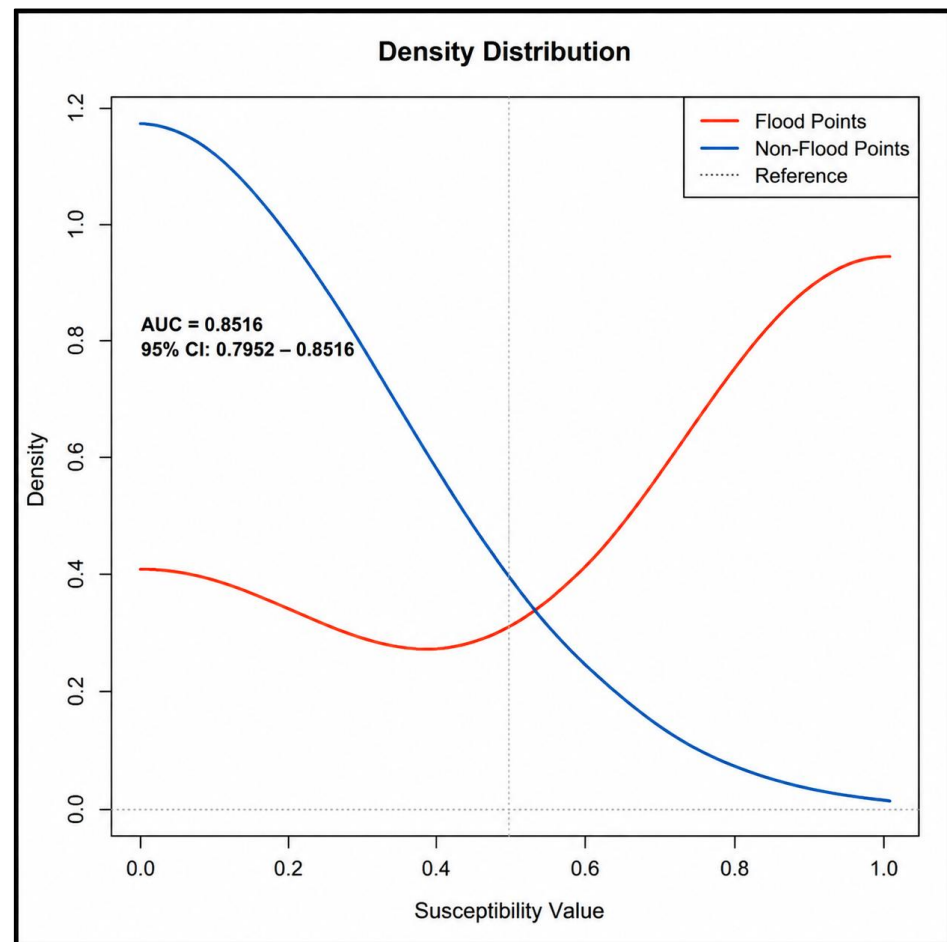


Figure 24. Density distribution of susceptibility values flood validation and non-flood reference points.

3.4. Model Performance Assessment

The predictive performance of the proposed ensemble flood susceptibility framework was evaluated using complementary threshold-dependent and threshold-independent validation metrics based on an independent historical flood inventory comprising 65 documented flood occurrence locations across KwaZulu-Natal. Together, the High-Susceptibility Capture Rate (HSCR) and Receiver Operating Characteristic (ROC) analysis provide empirical evidence for assessing the ability of the theoretical modelling framework to identify areas predisposed to flooding.

The HSCR analysis demonstrated that 73.85% of all documented flood locations were correctly classified within the High susceptibility class alone, while more than 90% occurred within the combined Moderate, High and Very High susceptibility classes. This result indicates that the ensemble framework successfully identified the dominant hydrogeomorphological conditions associated with historical flooding while avoiding excessive over-classification of the landscape into extreme hazard categories. The presence of a small proportion of flood occurrences within lower susceptibility classes is expected because flood susceptibility represents the long-term spatial predisposition to flooding rather than deterministic prediction of individual flood events, which are also influenced by antecedent soil moisture, rainfall intensity, drainage infrastructure, and other dynamic factors not explicitly represented in static susceptibility mapping [83,84].

Threshold-independent validation using ROC analysis yielded an Area Under the Curve (AUC) of 0.852 with a 95% confidence interval, indicating good discriminative ability between flood-prone and non-flood-prone locations [72]. The lower confidence bound

remained close to the widely accepted benchmark of 0.80 for good predictive performance [72], demonstrating that the observed model accuracy is statistically robust and unlikely to result from sampling variability. The relatively narrow confidence interval further indicates stable model performance across bootstrap resampling iterations and provides quantitative confidence in the reproducibility of the framework [73].

The validation results compare favourably with those reported in previous flood susceptibility studies employing ensemble and hybrid modelling approaches. Yilmaz [18] reported AUC values ranging between 0.82 and 0.88 for integrated AHP-frequency ratio models, while Danso, Ma and Addo [24] obtained an AUC of approximately 0.85 using an ensemble framework combining evidential belief functions and probabilistic approaches. Similarly, Tehrany, Jones and Shabani [34] suggested that AUC values exceeding 0.80 generally indicate reliable predictive capability for regional flood susceptibility mapping. The AUC of 0.852 achieved in the present study therefore falls well within the range reported for well-performing susceptibility models, demonstrating that the proposed framework performs comparably with established methodologies despite being applied over a large and hydro-climatically diverse province.

To provide empirical evidence supporting the proposed theoretical framework, model performance was evaluated using complementary validation metrics, namely the High-Susceptibility Capture Rate (HSCR = 73.85%) and the Area Under the Receiver Operating Characteristic Curve (AUC = 0.852). The combined use of threshold-dependent and threshold-independent validation metrics is widely recommended in flood susceptibility modelling because it provides a more comprehensive assessment of predictive performance than reliance on a single metric [34,69]. Whereas HSCR evaluates the practical ability of the model to correctly identify historically flood-affected locations within pre-defined susceptibility classes, ROC-AUC measures the model's overall discriminative capability independently of classification thresholds [71,72]. Agreement between both validation metrics indicates that the integration of topographic, hydrological, climatic, vegetation, and land-use conditioning factors within the ensemble modelling framework successfully captures the principal physical controls governing flood susceptibility across KwaZulu-Natal, consistent with previous flood susceptibility studies [48,79,85]. These findings therefore provide empirical support for the proposed conceptual framework, demonstrating that integrating deterministic expert knowledge through AHP with complementary modelling approaches enhances the ability of the model to reproduce independently observed flood occurrence patterns, consistent with the advantages reported for ensemble susceptibility modelling [34,69].

Overall, the validation demonstrates that the proposed framework is not merely a theoretical construct but a practically applicable flood susceptibility modelling approach capable of reliably identifying areas with elevated flood predisposition at a provincial scale. While future studies incorporating event-based hydrological variables, higher-resolution soil information, and more comprehensive flood inventories may further improve predictive performance, the current validation confirms that the framework provides a scientifically robust basis for regional flood risk assessment, land-use planning, and disaster risk reduction in data-scarce environments

3.5. Comparative Model Performance

The confusion matrix analysis revealed differences in predictive performance among the four susceptibility models (Table 9). The ensemble model achieved the highest overall accuracy (92.22%) and F1-score (80.49%), indicating the best balance between correctly identifying flood-prone areas and minimizing false classifications. The fuzzy logic model produced the highest recall (87.50%), demonstrating superior ability to identify historical flood locations, although this was accompanied by a larger number of false positives and

consequently lower precision. Conversely, the frequency ratio model achieved the highest precision (66.07%) and specificity (92.96%), indicating strong capability for correctly identifying non-flood locations but at the expense of lower recall due to increased false negatives. The AHP model exhibited balanced performance across all metrics, although slightly lower than the ensemble approach. These findings support the use of ensemble approaches for regional flood susceptibility assessment by reducing reliance on any single modelling paradigm.

Table 9. Quantitative comparison of flood susceptibility model performance.

Model	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)
AHP	85.63	58.70	84.38	85.93	69.23
Fuzzy	84.43	56.00	87.50	83.70	68.29
FR	86.23	66.07	57.81	92.96	61.67
Ensemble	92.22	76.94	84.38	94.07	80.49

3.6. Hydrological Interpretation of Susceptibility Patterns

The spatial distribution of flood susceptibility across KwaZulu-Natal reflects the combined influence of topographic controls, climatic forcing, drainage characteristics, land use, and hydrological connectivity rather than any single conditioning factor. Areas classified as highly susceptible are generally characterized by low-lying terrain, gentle slopes, high drainage density, and close proximity to river channels, where runoff converges and accumulates efficiently. These conditions are further intensified in regions receiving high mean annual rainfall, particularly along the eastern coastal belt and the escarpment, where frequent and intense precipitation generates large runoff volumes that exceed local drainage capacity. In contrast, the western interior and elevated Drakensberg regions generally exhibit lower susceptibility because steeper gradients promote more rapid downslope drainage, reducing the residence time of surface water despite locally high rainfall totals.

Land use further modifies these hydrological responses by influencing infiltration, surface roughness, and runoff generation. Urbanized areas within the eThekweni Metropolitan Municipality and other rapidly developing coastal centres contain extensive impervious surfaces that substantially reduce infiltration and increase the proportion of direct surface runoff, resulting in shorter catchment response times and higher flood potential. Conversely, natural vegetation and forested areas generally enhance interception, evapotranspiration, and infiltration, thereby attenuating runoff. The interaction between these land surface characteristics and the underlying drainage network enhances hydrological connectivity, allowing runoff generated on hillslopes to be rapidly transferred to stream channels. Consequently, catchments exhibiting a combination of high rainfall, dense drainage networks, low relief, limited infiltration capacity, and strong hillslope-channel connectivity consistently correspond to the highest flood susceptibility classes identified by all three models and the ensemble map. These findings demonstrate that flood susceptibility in KwaZulu-Natal is governed by the cumulative interaction of multiple hydrological processes, highlighting the importance of adopting an integrated multi-factor modelling framework.

3.7. Study Limitations

Despite the good predictive performance of the proposed framework, several methodological limitations should be acknowledged. First, the absence of high-resolution soil and geological datasets necessitated the use of slope-derived proxies for soil development and lithology. Although slope provides a reasonable first-order indicator of pedogenic

and geomorphological processes [51], it cannot explicitly represent spatial variations in soil texture, hydraulic conductivity, or geological permeability that directly influence infiltration and runoff generation.

Second, the climatic component was represented using mean annual rainfall (2010–2023), which does not capture the short-duration, high-intensity rainfall events that typically trigger flooding in KwaZulu-Natal. Consequently, the model reflects long-term climatic predisposition rather than event-specific flood generation. This limitation is illustrated by the April 2022 floods, which resulted from approximately 300–400 mm of rainfall over a 48 h period in a region with an average annual rainfall of approximately 1000 mm [5].

Third, drainage density was represented using a 2.5 km kernel mean filter to characterize regional drainage concentration. While appropriate for provincial-scale analysis, this approach generalizes local drainage network complexity and cannot fully represent small tributaries, artificial drainage systems, or local flow convergence that influence runoff concentration at finer spatial scales.

Fourth, all conditioning factors incorporated within the framework are essentially static, including topography, long-term rainfall, land use, and vegetation cover. Consequently, the resulting flood susceptibility index (FSI) represents the long-term spatial predisposition to flooding rather than the probability of flooding during individual storm events. Actual flood occurrence is also influenced by dynamic factors such as antecedent soil moisture, rainfall intensity and duration, reservoir operations, and drainage infrastructure performance, which were beyond the scope of this regional susceptibility assessment. An additional source of uncertainty arises from the expert-based weighting inherent in the Analytical Hierarchy Process (AHP). Although the pairwise comparison matrix achieved a consistency ratio ($CR = 0.03$), well below the recommended threshold of 0.10 [54,55], indicating logically consistent judgements, the assigned weights remain dependent on expert interpretation. Alternative experts or stakeholder groups may assign different relative importance to the conditioning factors, potentially producing different flood susceptibility patterns [56]. While the weighting scheme adopted in this study was informed by established hydrological literature and verified through consistency testing, some degree of subjectivity is unavoidable in expert-based multi-criteria decision-making. Future research should evaluate the sensitivity of the susceptibility maps to alternative weighting schemes or compare expert-derived weights with fully data-driven approaches, such as entropy weighting or machine learning-based feature importance, to quantify the influence of weighting uncertainty on model performance.

Fifth, the 30 m spatial resolution adopted for the analysis, while appropriate for provincial-scale susceptibility mapping, is insufficient to resolve fine-scale flood controls such as road culverts, stormwater infrastructure, small drainage channels, and plot-scale soil variability that are particularly important in urban environments [31]. Consequently, the framework is more appropriate for strategic regional planning than detailed site-scale flood assessments.

Additionally, uncertainty analysis demonstrated low inter-model variability, with pixel-wise standard deviation values ranging from 0.00 to 0.11, indicating strong agreement among modelling approaches. However, this interpretation acknowledges that the uncertainty metric primarily reflects divergence between knowledge-driven (AHP and Fuzzy) and data-driven (FR) approaches. Future research should explore additional uncertainty sources, including alternative model structures, factor weightings, and membership function parameterisations, to provide a more comprehensive uncertainty assessment.

Finally, the historical flood inventory used for model validation is subject to observational bias [86]. Flood records are concentrated in densely populated coastal municipalities where reporting systems and disaster response mechanisms are more developed, whereas flood occurrences in sparsely populated inland regions are more likely to be

underreported. Consequently, the spatial distribution of historical flood locations reflects not only the physical susceptibility to flooding but also patterns of population exposure, infrastructure distribution, and reporting capacity. Although this limitation is common to regional flood susceptibility studies, it should be considered when interpreting the validation results and the spatial distribution of model performance.

Overall, these limitations do not diminish the utility of the proposed framework for regional flood susceptibility assessment but instead identify opportunities for future refinement through the incorporation of higher-resolution environmental datasets, dynamic hydro-meteorological variables, alternative weighting strategies, and more comprehensive flood inventories.

4. Conclusions

This study developed and implemented a process-informed ensemble multi-criteria flood susceptibility modelling framework for KwaZulu-Natal, integrating Analytical Hierarchy Process (AHP), fuzzy logic transformation, and frequency ratio (FR) modelling within a cloud-based GIS environment. By harmonizing twelve hydro-geomorphological, climatic, and land surface conditioning factors through percentile-based normalization and structured weighting, the framework addressed key limitations associated with standalone deterministic or probabilistic approaches.

The AHP model produced susceptibility values ranging from 0.03 to 0.97, reflecting structured weighting, while the fuzzy model extended the upper susceptibility bound to 0.93, with more representation of gradual hydrological transitions. The ensemble integration moderated individual model biases, resulting in a final flood susceptibility index (FSI) ranging from 0.05 to 1.00. This aggregation improved spatial stability, reduced overestimation and underestimation tendencies, and enhanced generalization capability across heterogeneous catchments.

Uncertainty analysis demonstrated low inter-model variability, with pixel-wise standard deviation values ranging from 0.00 to 0.11, indicating good agreement among modelling approaches. The ensemble susceptibility map revealed that 51.08% of the province falls within the moderate susceptibility class, while 8.36% (High and Very High combined) represents critical high-risk zones. Although spatially limited, these high-susceptibility areas are hydrologically significant and warrant targeted intervention.

Validation using a 10-year historical flood inventory (2015–2025) demonstrated good predictive performance, with 73.85% of documented flood occurrences located within the High susceptibility class and more than 90% falling within susceptible zones overall. This confirms that the ensemble framework effectively captured dominant flood conditioning mechanisms in the province, including topographic convergence, drainage concentration, rainfall gradients, and land-cover influences.

Overall, the study demonstrates that integrating deterministic, fuzzy, and probabilistic approaches within an ensemble framework improves flood susceptibility representation, enhances spatial reliability, and provides a transparent uncertainty field. The methodology advances provincial-scale flood susceptibility assessment by embedding hydrological process understanding and uncertainty quantification into spatial hazard modelling, thereby supporting evidence-based disaster risk reduction and land-use planning. From a practical perspective, the generated flood susceptibility maps provide a valuable decision-support tool for disaster management agencies, municipal planners, water resource managers, and infrastructure authorities. High and Very High susceptibility zones can be prioritized for flood monitoring, early warning system deployment, drainage infrastructure upgrades, emergency preparedness planning, and land-use regulation. Furthermore, the cloud-based implementation using Google Earth Engine provides a scalable and reproducible framework that can be adapted to other provinces in South Africa

following local calibration and validation using regional flood inventories and environmental datasets.

5. Future Research Direction

Future research should prioritize enhancing the physical realism and predictive capability of flood susceptibility models in KwaZulu-Natal by integrating high-resolution soil and geological data to replace slope-based proxies, and by incorporating dynamic hydro-meteorological variables, such as event-based rainfall intensity and antecedent moisture, to facilitate a transition towards temporal hazard forecasting. Methodologically, the framework would benefit from the application of machine learning and explainable AI to capture complex nonlinear interactions, while the development of a standardized, georeferenced flood inventory using remote sensing is critical for robust model validation. Ultimately, extending the analysis beyond physical predisposition to include socio-economic exposure and vulnerability is essential for transforming susceptibility maps into integrated tools for holistic risk management and policy application. Finally, the NDVI-based vegetation correction represents current vegetation conditions and does not account for temporal changes in land cover caused by deforestation, urbanization, or climate-driven ecosystem changes. Incorporating multi-temporal satellite observations and land-cover change scenarios would improve future flood modelling applications.

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