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Multi-Criteria Analysis of Flood Susceptibility in Tropical Rural Areas: Application of the FIGUSED Model to the Kayanga Anambé Basin (Senegal)

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ABSTRACT: The Kayanga-Anambé watershed, located in Haute-Casamance (Senegal), is a strategic area for national food security, yet remains exposed to recurrent flooding that threatens hydro-agricultural developments. This study aims to map flood-susceptibility zones using an integrated approach combining Geographic Information Systems (GIS) with a multi-criteria model built on seven (7) parameters: Flow Accumulation, Rainfall Intensity, Land Use, Geology, Slope, Terrain Elevation, and Distance to drainage (FIGUSED). The methodology relies essentially on cross-referencing morphometric factors (slope, drainage density), climatic factors (rainfall intensity), and anthropogenic factors (land use, infrastructure). Data derived from digital elevation models and Sentinel-2 imagery were processed through an Analytic Hierarchy Process (AHP) to weight the influence of each parameter. The results highlight a strong susceptibility of the Anambé basin, exacerbated by gentle slopes and the rapid saturation of hydromorphic soils during monsoon peaks. The high-susceptibility zone (high and very high classes) totals 40.64% of the watershed area, that is 1257.46 km², corresponding geographically to the Anambé basin and the floodplain of the Kayanga and its tributaries. The most represented class is high susceptibility, at nearly 28%, closely followed by moderate susceptibility at 25.52% of the total area, indicating an overall heightened susceptibility of the watershed to inundation. The resulting susceptibility map thus constitutes an essential decision-support tool for planning agricultural campaigns through SODAGRI and for protecting human settlements in tropical rural areas.

Keywords: Flooding; FIGUSED; GIS; Kayanga-Anambé; Senegal; Multi-criteria analysis

1. Introduction

At the global scale, tropical hydrosystems are under unprecedented pressure from intensifying climate extremes, threatening the safety of populations and the sustainability of infrastructure [1]. In West Africa, this dynamic translates into a paradoxical increase in flood frequency despite persistent drought episodes [2]. These disasters generate devastating socio-economic impacts, particularly in rural economies whose

subsistence depends on inherently vulnerable rainfed and irrigated agriculture [3]. The complexity of the West African monsoon, marked by strong spatio-temporal variability, makes flood genesis particularly difficult to anticipate [4]. Despite monitoring efforts, traditional forecasting methods struggle to account for the realities of transboundary rural watersheds, which are marked by a chronic scarcity of observational data. At the same time, land pressure and the search for fertile land push agricultural activities into the heart of floodable floodplains, mechanically increasing risk exposure.

In Senegal, the Haute-Casamance region perfectly illustrates this dynamic of vulnerability. Under the influence of a Sudano-Guinean hydrological regime, this territory records massive peak discharges during monsoon retreat [5]. At the heart of this system, the Kayanga-Anambé watershed carries strategic national importance, hosting the country's largest rice-growing perimeters developed under SODAGRI's aegis. However, this agricultural development hub is weakened by the progressive silting of waterways, changes in vegetation cover, and emerging urbanization in secondary centres [6,7]. Water regulation is complex there, as the Niandouba and Confluent dams profoundly alter the propagation of flood waves downstream [8]. Historical floods recorded in the area have repeatedly undermined agricultural production objectives and strained the resilience of rural communities [9,10].

In the absence of dense *in-situ* measurement networks, spatial remote sensing and Geographic Information Systems (GIS) stand out as indispensable alternatives for mapping floodable zones [11–14]. Integrating these geospatial variables into Spatial Multi-Criteria Analysis (MCA) frameworks, particularly the Analytic Hierarchy Process (AHP) developed by [15], enables rigorous hierarchisation of hazard and vulnerability factors by weighting their relative importance. Widely tested in West Africa for flood-risk mapping, whether in urban settings in Dakar [16] and Abidjan [17], or at the scale of large rural watersheds such as the Bandama [18], the Ouémé [19], and the Mono [20], the AHP-GIS approach offers a robust mathematical structure to compensate for the scarcity of streamflow time series.

It is within this methodological approach that the FIGUSED model is applied, originally designed by [21] to assess flood susceptibility from seven physical and anthropogenic parameters (Flow accumulation, Rainfall Intensity, Geology, Land Use, Slope, Elevation, Distance from drainage). While this AHP-based index model has been the subject of various applications in West Africa [22], its recent adaptations in the Senegalese context demonstrate its operational relevance: Ref. [23] tested its effectiveness for modelling flood risk in the dense urban setting of the Thiès basin, while [24] applied it to analyse the vulnerability of irrigated banana plantations along the Gambia River in Tambacounda. The application of the FIGUSED model to the Kayanga-Anambé watershed, however, addresses a distinct and unprecedented challenge: assessing flood susceptibility in a complex hydro-agricultural basin where the flatness of the relief, hydraulic control by dams, and intensive rice farming redefine the propagation of the hazard.

The major contribution of this work, therefore, lies in the regionalisation and adaptation of the FIGUSED model to the hydro-morphological and anthropogenic specificities of a Sudano-Guinean basin under strong agricultural pressure. By offsetting the lack of surface hydrometric data through the combined use of CHIRPS data, the SRTM DEM, and Saaty's AHP process, this study provides a structured account of flooding mechanisms in tropical rural areas. To address this challenge, the research is built around three central questions:

To what extent do local geomorphological factors (slope, elevation, drainage) predominate over anthropogenic factors (land use, SODAGRI developments) in the genesis of water-accumulation zones within the Anambé basin?

How does the integration of FIGUSED model variables within a GIS environment faithfully render the spatial distribution of flood susceptibility in a context of scarce *in-situ* data?

What is the predictive value and reliability of the FIGUSED model when confronted with empirical field data and historical flood records reported by local populations?

To better structure this work and provide a coherent response to these different questions, the article is organised as follows. Section 2 reviews the relevant literature on flood-risk mapping approaches and on the FIGUSED model. Section 3 presents the study area. Section 4 describes the Materials and Methods: the spatial data sources used (CHIRPS, SRTM, Sentinel-2) and the methodological workflow of the FIGUSED-AHP model. Section 5 presents the Results: the thematic mapping of the seven criteria, the calculation of relative weights, the final Flood Susceptibility Index map, and its empirical validation. Section 6, the Discussion, analyses the scope of the results, situates the model's performance relative to previous work in West Africa, and discusses its limitations as well as its applications for land-use planning. Finally, Section 7, the Conclusion, synthesises the main findings and formulates operational recommendations for securing hydro-agricultural investments in Haute-Casamance.

2. Literature Review

2.1. Evolution of Flood-Risk Mapping Approaches in Tropical Settings

Historically, flood-risk characterisation relied mainly on deterministic, physically based hydrological and hydraulic models (HEC-RAS, SWMM), fed by discharge and rainfall time series [25]. While these approaches offer high temporal precision, their application in tropical rural areas is hindered by the scarcity and spatio-temporal discontinuity of *in-situ* gauging networks [26,27]. To overcome the obstacle of “ungauged basins”, the advent of spatial remote sensing and Geographic Information Systems (GIS) has revolutionised the spatial analysis of hazards [28]. Satellite imagery now enables continuous characterisation of the physical factors of the environment, such as topography via Digital Elevation Models (SRTM, ALOS PALSAR) or land-use dynamics via the Landsat and Sentinel missions [29].

2.2. Spatial Multi-Criteria Analysis (AHP-GIS) Applied to Flood Risk

The integration of remote-sensing data into Multi-Criteria Decision Analysis (MCDA) models has become a scientific standard for the empirical assessment of flood susceptibility [30]. Among these methods, the Analytic Hierarchy Process (AHP) developed by [15] is the most widely applied for hierarchising heterogeneous criteria [31]. In West Africa, numerous studies have demonstrated the effectiveness of coupling AHP with GIS to map floodable areas, notably in Nigeria [32] and in Senegal [16]. Nevertheless, the literature emphasises that the reliability of these models depends on a rigorous selection of predictive variables and their validation against field data [33].

2.3. The FIGUSED Conceptual Model: Origins, Foundations, and Adaptations

To formalise and standardise the selection of predictive factors, the FIGUSED conceptual model or its sensitivity-validated variant, FIGUSED-S was formalised by [21]. This index-based model integrates seven major environmental parameters, namely:

- ❖ Flow accumulation (F): accumulation of runoff flows;
 - ❖ Intensity of rainfall (I): rainfall intensity (triggering hazard), operationalised in this study as the mean annual rainfall total, in the absence of sub-daily precipitation records;
 - ❖ Geology (G): lithology and permeability of the substrate;
 - ❖ Land Use (U): land occupation and development;
 - ❖ Slope (S): terrain slope and steepness;
 - ❖ Elevation (E): altitude and basin morphology;
 - ❖ Distance to drainage network (D): proximity to the hydrographic network.
- Initially designed for regional-scale risk assessment [21], the FIGUSED model has proven particularly effective in West African basins subject to the monsoon regime. In Senegal, the application of the FIGUSED method by [23] in the Thiès watershed demonstrated the strong sensitivity of hazard to gentle

slope gradients and proximity to drainage networks. Likewise, the recent work of [24] confirmed the effectiveness of the FIGUSED-AHP approach for assessing flood risk in the irrigated banana perimeters of Tambacounda, underscoring the predominant role of flat topography in rainwater stagnation.

2.4. *The Kayanga-Anambé Basin: Hydro-Agricultural Specificities and Vulnerability*

Although the FIGUSED model has proven its robustness in various basins across the region, its application to the Kayanga-Anambé basin requires accounting for particular hydro-morphological and anthropogenic dynamics.

Hydrological regime and regulation: The foundational studies of [34] point to a regime marked by large late-monsoon floods. In the Anambé basin, the presence of SODAGRI's hydro-agricultural infrastructure (the Niandouba and Confluent dams) has profoundly altered natural flows and the propagation of flood waves [35].

Topography and stagnation: As highlighted by [23,24] for similar Senegalese contexts, the predominance of very gentle slopes (<1%) and low-lying receiving elevations makes flow accumulation (F) and elevation (E) critical explanatory factors of inundation.

Anthropogenic pressure (developments) and rice-growing stakes (irrigation): The transformation of natural wetlands into developed rice-growing plots (Land Use, U) directly alters soil roughness and water retention [6,7]. During exceptionally rainy seasons, the inability of the drainage network (D) to evacuate excess water causes prolonged flooding that devastates rice plots within the developed perimeter as well as across the valley.

This literature review shows that adapting the FIGUSED model to the Kayanga-Anambé basin addresses a specific scientific gap: assessing flood susceptibility in a flat, strongly anthropised, and regulated basin, where hazard depends not solely on the overflow of the main watercourses, but on the conjunction of saturation of hydro-agricultural developments, surface runoff, and morphological constraints.

2.5. *Complementary Operations-Research and Climate-Projection Perspectives on Flood Risk*

Beyond susceptibility mapping, a broader strand of literature extends flood-risk research toward data-driven prediction and the operational management of the disaster response, against which the hazard-mapping focus of the present study can be situated. Ref. [36] proposed machine-learning models, including Random Forest and Adaptive Neuro-Fuzzy Inference System architectures, to estimate flood magnitude from fifty years of hydrological data in the Sefidrud River basin, illustrating the growing role of data-driven approaches as a complement to physically based and index-based models such as FIGUSED. Downstream of hazard mapping, several works address the operational management of the disaster response itself: Ref. [37] proposed a multi-objective robust-stochastic optimisation model to plan the distribution of relief goods under uncertainty, validated on a flood case study in Bangladesh, while Ref. [38] analysed the joint redesign of demand and service selection in freight transportation networks facing disruption, and Ref. [39] examined post-disaster recovery planning for scheduled service networks using temporary capacity configurations. Upstream, at the scale of climate projections, Ref. [40] proposed a Soil and Water Assessment Tool framework driven by several General Circulation Models under different Representative Concentration Pathways to analyse the impact of climate change on river streamflow. Taken together, these contributions delineate the wider chain, from climate projection to hazard mapping and disaster-response logistics, within which the present FIGUSED-based assessment of the Kayanga-Anambé basin is positioned as the hazard-mapping link.

3. Presentation of the Study Area

The Kayanga-Anambé watershed is located in Haute-Casamance, in the Kolda administrative region in southern Senegal, extending between latitudes 12°40' and 13°15' North and longitudes 13°40' and 15°00' West. This transboundary system, whose headwaters lie on the foothills of the Fouta Djallon in Guinea, covers a strategic area of 3095 km². Shared by fifteen (15) municipalities, the basin links the departments of Vélingara and Kolda (Figure 1). The relief of the area is marked by a contrast between low-altitude plateaus (10 to 100 m) and a vast alluvial plain known as the “Anambé Basin”. The geomorphology of this basin is characterised by extremely gentle slopes, often below 2%, which considerably reduces drainage velocity and favours the spreading of water during flood episodes. In terms of soils, there is a clear transition between the leached tropical ferruginous soils of the plateaus and the clay-rich hydromorphic soils of the lowlands. The Sudano-Guinean climate is punctuated by a rainy season (June to October) delivering between 700 and 1100 mm of annual rainfall. Hydrology is dominated by the Kayanga River and its natural tributary, the Anambé, whose courses have been profoundly altered by SODAGRI developments, notably the Niandouba and Confluent dams. The Niandouba dam serves as a water-storage reservoir for the SODAGRI agricultural perimeter, while the upstream Confluent dam has altered the natural hydraulic connectivity of the Anambé to the point of converting it from a tributary (affluent) of the Kayanga, its original role, into a distributary (défluent). These structures, designed for agricultural water control, create new management challenges during periods of peak rainfall. Land use is characterised by a trend of deforestation in favour of extensive agriculture, which, combined with the urbanisation of riverside villages, increases the watershed’s vulnerability to recurrent flooding.

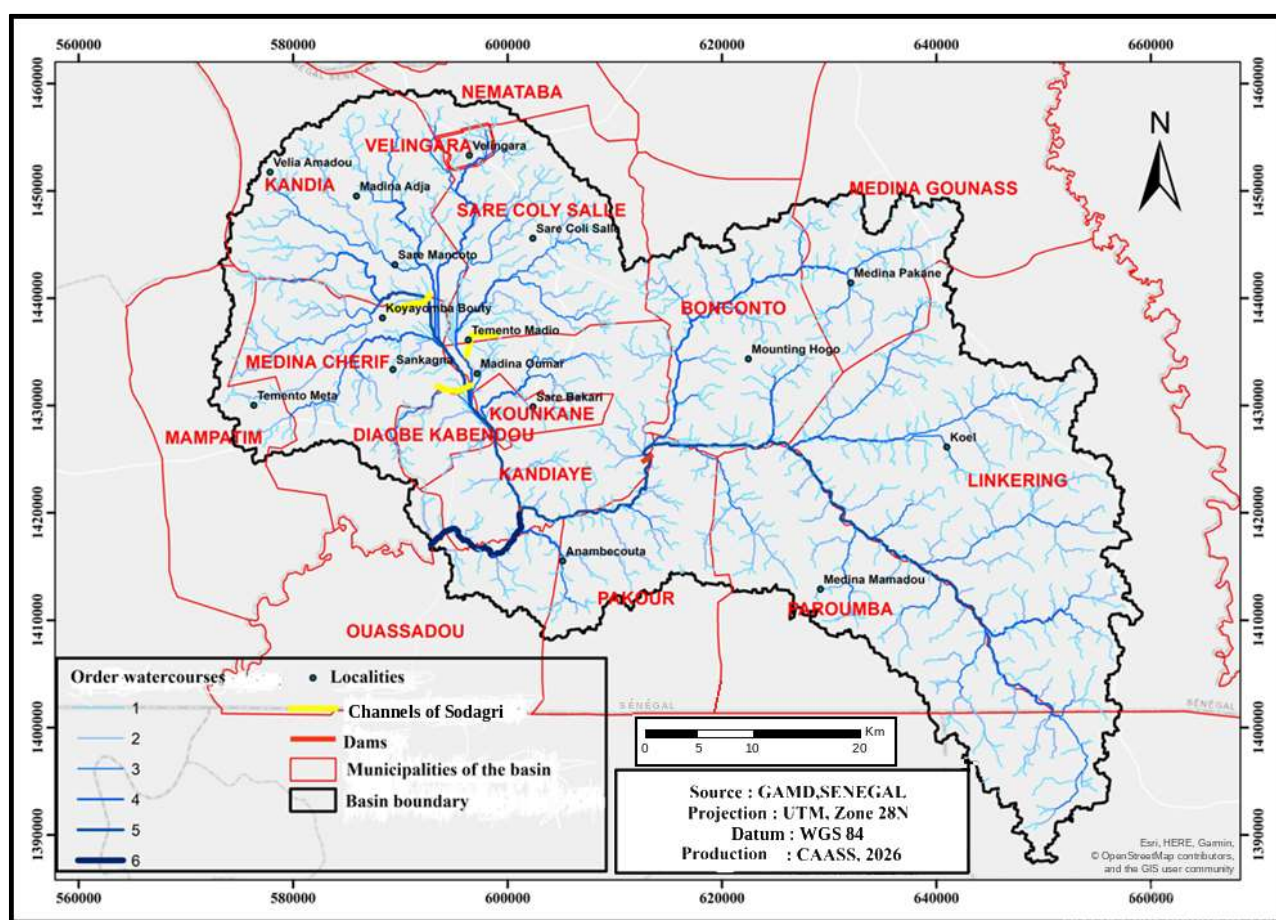


Figure 1. Location of the Kayanga Anambé basin (Source: Global Administrative Areas: Senegal, 2025).

4. Materials and Methods: The FIGUSED Method

The FIGUSED method (Flow accumulation, rainfall Intensity, Geology, land Use, Slope, Elevation, Distance from drainage), a model formalised by [21], is a multi-criteria approach for assessing flood susceptibility in a geographic environment using Geographic Information Systems (GIS). This method makes it possible to model flood susceptibility by accounting for several environmental and anthropogenic parameters. The six sub-sections that follow correspond to the successive steps of the workflow shown in Figure 2: the geospatial data collected, the susceptibility-assessment parameters derived from these data, the construction and weighting of the pairwise comparison matrix, the resulting flood-susceptibility mapping, the sensitivity analysis of the model's weights, and the validation of the results. The following steps describe the materials and methodology used to apply this method:

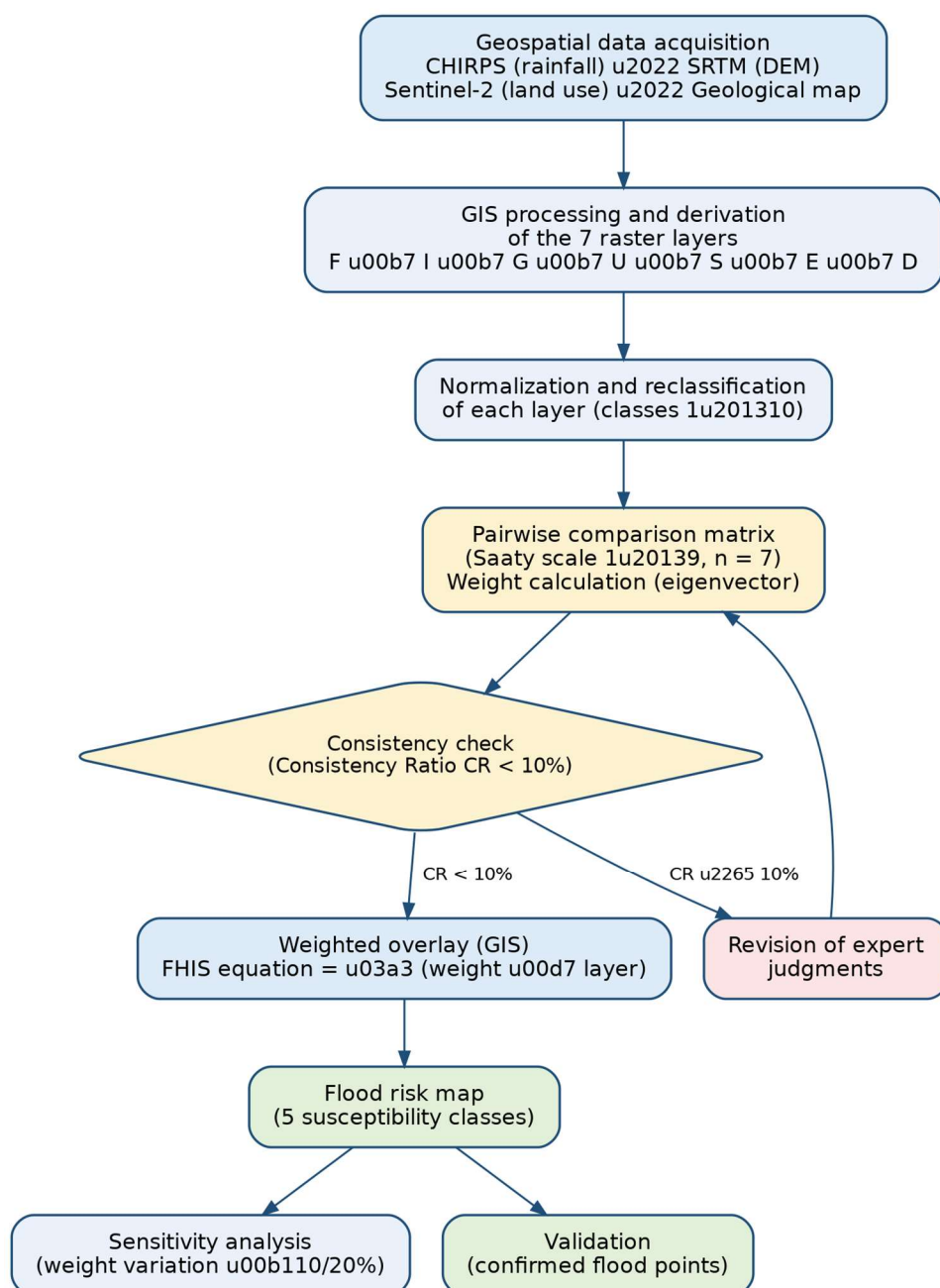


Figure 2. Methodological flowchart of the FIGUSED-AHP model applied to the Kayanga-Anambé basin.

Figure 2 details and justifies the seven implementation steps followed to derive the FHIS map. Step 1 (Geospatial data acquisition) gathers the four raw sources described in Section 4.1: CHIRPS rainfall, the SRTM DEM, Sentinel-2 imagery, and the BGS geological map. Step 2 (GIS processing) derives the seven FIGUSED raster layers (F, I, G, U, S, E, D) from these sources in ArcGIS. Step 3 (Normalisation and reclassification) rescales each layer onto the common five-level susceptibility scale (2, 4, 6, 8, 10) used for parameter scoring, so that parameters expressed in different physical units become comparable. Step 4 (Pairwise comparison matrix) applies the Saaty scale to build the 7×7 matrix and compute the AHP eigenvector weights as detailed in Section 4.3. Step 5 (Consistency check) verifies that the Consistency Ratio of this matrix remains below the 10% threshold judgments are revised and the matrix rebuilt if this condition is not met, which is why the diagram loops back from the consistency-check step to the pairwise-matrix step. Step 6 (Weighted overlay) combines the seven normalised layers through the FHIS equation to produce the flood-susceptibility map in five classes (Section 4.4). Step 7 branches into two complementary checks presented in Sections 4.5 and 4.6: the sensitivity analysis, which tests the map's robustness to variations in AHP weights, and validation against confirmed flood points.

4.1. Data Collection

The success of applying the FIGUSED method rests on the acquisition and analysis of diverse geospatial and environmental data. The main data sources are as follows (Table 1):

Rainfall data: Rainfall data are essential for understanding the distribution of precipitation across the study area. Such data can be collected from local weather stations or public databases, such as those provided by national meteorological services. In this study, CHIRPS data at 5.5 km spatial resolution were used over the period 1981–2025, downloadable at the following link: (<https://climateengine.org/>, accessed on 1 August 2026).

Topographic data: Topographic maps and elevation data (Digital Elevation Models, DEM) are used to determine terrain altitude and slope. This information is essential for modelling runoff and identifying low-elevation areas prone to flooding. The data were obtained from satellite imagery: SRTM (Shuttle Radar Topography Mission) 30 m from NASA, freely downloadable from USGS earthexplorer.usgs.gov (accessed on 1 August 2026) or via Google Earth Engine (GEE).

Satellite imagery: Satellite images such as Landsat or Sentinel enable mapping of land cover, vegetation cover, infrastructure, and hydrographic networks. These images are used to detect environmental changes and observe specific geographic features (such as building density) [41]. In this study, Sentinel-2 Level-2A (bottom-of-atmosphere reflectance) imagery from the COPERNICUS/S2_SR_HARMONIZED collection was used via Google Earth Engine (GEE) to map land use across the Kayanga-Anambé basin. Images from the November 2024–May 2025 dry-season window were filtered to a cloud cover below 15% and masked for clouds using the Scene Classification Layer (SCL). A cloud-free composite was built from the temporal median of bands B2, B3, B4, B8, B11, and B12 (10 m/20 m native resolution, resampled to 10 m), complemented by four spectral indices (NDVI, EVI, MNDWI, NDBI) computed to improve class separability. A Random Forest classifier (100 trees) was trained on a stratified sample of 3600 points (2538 for training, 1062 for validation) to discriminate five land-cover classes, followed by a 3×3 majority filter to remove salt-and-pepper noise.

Drainage maps: Information on drainage networks (canals, rivers, ditches) is collected to assess their capacity to manage water flow and to identify congestion zones within the drainage network that may cause flooding [42]. It is derived from SRTM elevation data (Shuttle Radar Topography Mission), 30 m resolution, freely downloadable from earthexplorer.usgs.gov. It provides the altitude of each pixel, enabling ArcGIS to compute slope and the direction of gravity-driven water flow.

The Flow Accumulation (F) layer was computed in ArcGIS 10.8 from the Flow Direction raster (D8 method) using the Flow Accumulation tool, producing for each cell the number of upslope cells draining

into it through gravitational flow (a dimensionless quantity, indicative of contributing area, not an actual water volume). The five classes used in were obtained by direct reclassification of this raw raster using the Jenks Natural Breaks method (Reclassify, ArcGIS 10.8).

Geological data: The Geology (G) layer was built from the British Geological Survey's Africa Groundwater Atlas Country Hydrogeology Maps (geology theme, scale 1:5,000,000 [43]), derived from the Africa-wide geological map of [44], digitised by [45], and reclassified according to the relative permeability of the geological formations present across the basin.

Beyond their simple description, these four datasets underwent specific analytical pre-processing before their integration into the FIGUSED model: the CHIRPS series (1981–2025) was aggregated to compute the mean annual rainfall total, used to build the rainfall (I) layer; the 30 m SRTM DEM was processed in ArcGIS (depression filling, flow-direction computation) to derive the Slope (S), Elevation (E), Flow Accumulation (F), and Distance to Drainage Network (D) layers; the Sentinel-2 image was classified using a Random Forest supervised classifier to produce the Land Use (U) layer; and the lithological nature of the substrate allowed the Geology (G) layer to be reclassified according to its relative permeability.

The reliability of the Land Use (U) classification was assessed using a confusion matrix computed on the independent 30% validation sample, reporting an Overall Accuracy of 68.3% and a Kappa coefficient of 0.637, indicating a substantial level of agreement [46].

Table 1. Summary of the geospatial datasets used, their native and final characteristics, pre-processing, and role in the FIGUSED model.

Dataset	Source and Period	Native Resolution	Final Resolution and Projection	Pre-Processing Applied	Layer(s) Produced
CHIRPS	climateengine.org, 1981–2025	~5.5 km (0.05° grid, native WGS84 geographic)	30 m, UTM Zone 28N, WGS84	Aggregated daily series to mean annual rainfall total; reprojected and resampled to 30 m	Rainfall (I)
SRTM	NASA, via USGS EarthExplorer/Google Earth Engine	30 m (native)	30 m, UTM Zone 28N, WGS84	Depression filling; flow-direction and flow-accumulation computation	Elevation (E), Slope (S), Flow Accumulation (F), Distance to Drainage (D)
Sentinel-2	ESA, via GEE (COPERNICUS/S2_S R_HARMONIZED), November 2024–May 2025	10 m (B2, B3, B4, B8); 20 m (B11, B12)	30 m, UTM Zone 28N, WGS84	SCL cloud masking; temporal median composite; Random Forest classification (100 trees); 3 × 3 majority filter; resampled to 30 m	Land Use (U)
BGS Africa Groundwater Atlas Country Hydrogeology Maps (geology theme)	British Geological Survey, 2021 (base map: Furon & Lombard 1964, UNESCO/ASGA; digitised by USGS, Persits et al. 2002)	1:5,000,000 (map scale)	30 m, UTM Zone 28N, WGS84 (vectorised then rasterised)	Reclassified by relative soil permeability; rasterised	Geology (G)

All four datasets were harmonised onto a common 30 m analysis grid in UTM Zone 28N (WGS84), matching the native resolution of the SRTM DEM, prior to their integration into the weighted overlay described in Section 4.4.

4.2. Susceptibility Assessment Parameters

The FIGUSED method relies essentially on the integration of several parameters to assess flood susceptibility. These criteria may include, but are not limited to:

- ❖ Flow accumulation: This parameter is derived exclusively from the Digital Elevation Model (DEM) and represents, for each cell, the number of upslope cells draining into it through gravitational flow (contributing area), rather than an actual water volume; it constitutes an indirect indicator of surface-flow convergence axes, without directly incorporating rainfall data.
- ❖ Distance to drainage network: The proximity of areas to drainage networks influences their flood vulnerability. Areas close to drainage and water-evacuation canals face much higher risk than areas farther from them, owing to their direct exposure to overflow.
- ❖ Terrain altitude and slope: Low-lying or gently sloping areas are more prone to flooding, as water accumulates there more readily [47,48].
- ❖ Land use: Urbanisation, agriculture, and vegetation types affect soil capacity to absorb water and alter runoff characteristics [12,13,49].
- ❖ Rainfall intensity: The intensity and frequency of precipitation are key factors in flood analysis.
- ❖ Soil geology: The nature of the soil, whether impermeable or permeable, affects water infiltration capacity and influences flood risk [31].

4.3. Multi-Criteria Analysis Through the Construction of a Pairwise Comparison Matrix Applied to the FIGUSED Model

Within the multi-criteria analysis for mapping flood-susceptibility zones, determining the weights of the various environmental factors is a crucial step. This section describes the rigorous methodological protocol, structured in 6 steps, used to design and validate the pairwise comparison matrix for the FIGUSED model (Flow accumulation, Intensity of rainfall, Geology, Land Use, Slope, Elevation, Distance from drainage) applied to the Kayanga-Anambé basin.

4.3.1. Definition of Criteria and Hierarchy

The overall objective is to map the Flood Hazard Index Map (FHIS). To this end, the main challenge is broken down into a pyramidal hierarchical structure, namely:

- ❖ Level 0 (Objective): flood-susceptibility assessment
- ❖ Level 1 (FIGUSED criteria):
 -  F (Flow accumulation): zone of convergence of runoff flows
 -  I (Intensity of Rainfall): triggering climatic hazard
 -  G (Geology): soil permeability and lithology
 -  U (Land Use): impact of land occupation on runoff
 -  S (Slope): role of steepness in water stagnation and evacuation
 -  E (Elevation): basin morphology
 -  D (Distance From Drainage): proximity to watercourses and flow axes
- ❖ Level 2 (alternatives): GIS pixels or spatial units

4.3.2. Saaty Comparison Scale

To quantify qualitative expert judgments, the standard Thomas Saaty semantic and numerical scale (1 to 9) was used.

Table 2 is the reference grid used throughout Section 4.3: the “Hydrological Explanation/Justification” column translates Saaty’s generic semantic categories into the specific hydro-morphological reasoning

applied by the expert panel to the Kayanga-Anambé basin, and it is this hydrologically grounded version of the scale that produced the pairwise judgments recorded in Table 3.

Table 2. Saaty's semantic and numerical pairwise comparison scale.

Numerical Intensity	Semantic Definition	Hydrological Explanation/Justification
1	Equal importance	Both parameters have the same influence on flood triggering.
3	Moderate importance	Experience shows a slight dominance of one factor over the other.
5	Strong importance	One parameter clearly influences flood proneness far more (e.g., elevation vs. geology).
7	Very strong importance	The dominance of one factor is evident and confirmed by flood history.
9	Extreme importance	The importance of one parameter over the other is absolute (technical limit of assessment).
2, 4, 6, 8	Intermediate values	Allow nuance between two levels of the scale.

Table 3. Final comparison matrix validated according to the Saaty scale.

Parameters	F	I	G	U	S	E	D
F (Flow Acc.)	1	2	3	2	1/2	1/3	1/2
I (Rainfall)	1/2	1	2	2	1/3	1/4	1/3
G (Geology)	1/3	1/2	1	1	1/4	1/5	1/4
U (Land use)	1/2	1/2	1	1	1/4	1/5	1/4
S (Slope)	2	3	4	4	1	1/2	1
E (Elevation)	3	4	5	5	2	1	2
D (Distance)	2	3	4	4	1	1/2	1

4.3.3. Collection of Judgments and Consensus Method (Delphi)

To eliminate individual bias, the pairwise comparison matrix was built through a Delphi-based expert consultation involving seven experts: two hydrologists (university lecturer-researchers), one hydrogeologist (SODAGRI), two geographers, and two agronomists (SODAGRI). The consultation was structured around three workshops held at SODAGRI, spaced approximately two months apart, following the classic Delphi principle of iterative rounds with feedback between experts:

- ❖ Formulation of binary questions: experts state their judgment on each pair of criteria (e.g., between elevation and land use, which factor predominates in the Anambé basin?);
- ❖ Consensus building: individual judgments and their divergences were shared with the panel between workshops, allowing experts to revise their positions in light of the group's reasoning; by the third workshop, the panel reached a collectively discussed consensus for each pairwise comparison, which was entered as the final value in the matrix.

Thus, for a matrix of dimension $n = 7$, the total number of unique comparisons required amounts to:

$$N = n(n - 1)/2 = 7 \times 6/2 = 21 \text{ unique comparisons.}$$

4.3.4. Mathematical Construction of the Matrix

The reciprocal square matrix A (7×7) is structured according to three fundamental mathematical principles:

- ❖ Identity (diagonal): any criterion compared to itself equals 1 ($a_{ii} = 1$).
- ❖ Reciprocity: if $a_{ij} = x$, then $a_{ji} = 1/x$.
- ❖ Rigorous completion: the upper-right part contains the 21 empirical judgments, and the lower-left part is automatically completed by reciprocity.

4.3.5. Weighting and Consistency Analysis

Weights obtained from the pairwise comparison matrix (Table 3): for each parameter, the normalised principal eigenvector of the matrix, computed numerically (Saaty's method), directly gives its relative weight in the FHIS index. This method is distinct from the row geometric-mean approximation, sometimes used as a simplified substitute but mathematically different, to which it converges closely without being strictly identical.

Statistical validation of the comparison matrix makes it possible to verify that the expert judgments recorded in the pairwise comparison matrix (Table 3) are consistent enough to be used: the Consistency Ratio (CR), obtained by dividing the Consistency Index (CI) by the Random Index (RI) corresponding to a matrix of the same dimension ($n = 7$), must remain below the conventional threshold of 10% [15] for the matrix to be accepted without further expert consultation.

With a Consistency Ratio of 1.10%, far below the 10% acceptance threshold, Table 4 confirms that the expert judgments recorded in the pairwise comparison matrix (Table 3) are not contradictory and that the resulting weights (Table 5) can be used without further expert consultation, which is why the workflow in Figure 2 proceeds directly to the weighted overlay step rather than looping back to a revision of expert judgments.

Table 4. Consistency check of the pairwise comparison matrix.

Consistency Indicators	Abbreviation	Value
Number of criteria	n	7
Max eigenvalue	$(\lambda \text{ max})$	7.087
Consistency Index	(CI)	0.0145
Random Index	(RI)	1.32
Consistency Ratio	(CR)	1.10%
Verdict: Excellent consistency	CR	(<10%)

Table 5. Relative weights of the FIGUSED parameters derived from the AHP eigenvector.

FIGUSED Parameters	Eigenvector	Weight (%)
E (Elevation)	0.3145	31.45%
S (Slope)	0.1977	19.77%
D (Drainage Distance)	0.1977	19.77%
F (Flow accumulation)	0.1148	11.48%
I (Rainfall)	0.0766	7.66%
U (Land use)	0.0511	5.11%
G (Geology)	0.0476	4.76%

Final GIS integration equation (Raster Calculator):

$$\text{FHIS} = (0.1148 \times F) + (0.0766 \times I) + (0.0476 \times G) + (0.0511 \times U) + (0.1977 \times S) + (0.3145 \times E) + (0.1977 \times D)$$

The relative importance weights of each of the seven parameters, obtained from the pairwise comparison matrix (Table 5), were then applied to the corresponding normalised raster layers according to the FHIS equation presented above.

4.4. Flood Mapping

Concretely, the seven raster layers (F, I, G, U, S, E, D), previously reclassified onto a common five-level susceptibility scale (2, 4, 6, 8, 10), were combined in the Raster Calculator according to the FHIS equation, producing a continuous score per pixel. ArcGIS software (ArcMap 10.8) was used to perform the classification applying the Jenks (Natural Breaks) method. This method is widely used and provides an optimal statistical compromise for real geographic datasets, which are rarely uniformly distributed, by

minimizing within-class variance and maximizing between-class variance. Overlaying these various information layers within a GIS generates a comprehensive flood susceptibility map classified into different susceptibility levels (very low, low, moderate, high, and very high). This enables the visualization of susceptible areas in a spatially precise format, thereby facilitating decision-making for local authorities and urban planners.

4.5. Sensitivity Analysis

To verify the robustness of the FIGUSED model against the share of subjectivity inherent to the expert judgments used in the pairwise comparison matrix, a one-at-a-time (OAT) sensitivity analysis was conducted: the weight of each dominant parameter was, in turn, increased and then decreased by 10% and 20% relative to its reference value (Table 5), with the other six weights renormalised proportionally to preserve a unit sum, and the resulting effect on the FHIS score was assessed for each scenario. This procedure aims in particular to check whether Elevation (E) and Slope (S), which together account for more than half of the total weight (Table 5), excessively dominate the model's structure, or whether the ranking of susceptibility zones remains broadly stable.

Rather than re-running the full weighted overlay for each perturbation scenario, the sensitivity of the FHIS score to a change in weight can be bounded analytically. For a parameter with weight w subjected to a variation Δw (the other six weights being renormalised proportionally), the resulting shift in the FHIS score of any pixel is bounded by $|\Delta \text{FHIS}| \leq \Delta w \times (\text{score}_{\max} - \text{score}_{\min}) = \Delta w \times 8$, since each of the seven FIGUSED parameters is scored on a 2–10 scale (Table 6). Table 7 applies this bound to the three dominant parameters (Elevation, Slope, Drainage Distance), which together carry 71% of the total AHP weight (Table 5).

Table 6. Parameter values of the FIGUSED method.

Parameters	Classes	Rank	Area (km ²)	Share (%)
F: Flow accumulation	0–1	2	3115.170	99.656
	1–3	4	3.608	0.115
	3–5	6	4.193	0.134
	5–7	8	1.419	0.045
	7–9	10	1.548	0.050
I: Rainfall intensity	857–915	2	549.784	17.590
	915–958	4	905.273	28.964
	958–999	6	842.244	26.948
	999–1049	8	581.239	18.597
	1049–1122	10	246.959	7.901
G: Geology	Cretaceous-Quaternary sedimentary	2	2907.107	93.001
	Upper Proterozoic dominantly metasedimentary	4	83.789	2.680
	Neoproterozoic metamorphic complex	6	3.774	0.120
	Cambrian sedimentary	8	23.782	0.760
	Hercynian orogen	10	107.422	3.436
U: Land use	Cropland	2	792.948	25.374
	Hydrographic network	4	103.938	3.326
	Built-up	8	535.596	17.139
	Vegetation	6	1651.965	52.862
	Bare soil	10	40.623	1.300
S: Slope	0–1	10	1644.862	52.821
	1–2	8	713.990	22.928
	2–3	6	393.407	12.633
	3–5	4	308.967	9.921
	5–34	2	52.781	1.694

E: Elevation	22–38	10	502.643	16.080
	38–51	8	577.423	18.472
	51–62	6	712.087	22.780
	62–72	4	862.117	27.580
	72–96	2	471.610	15.087
D: Distance to drainage	1–4	10	1553.304	49.736
	4–6	8	1210.445	38.758
	6–7	6	295.708	9.468
	7–8	4	58.992	1.889
	8–10	2	4.631	0.148
FIGUSED: Flood susceptibility	3.60–5.28	Very Low	475.876	15.379
	5.28–6.70	Low	571.405	18.467
	6.70–7.88	Moderate	789.526	25.516
	7.88–9.07	High	862.922	27.888
	9.07–10.00	Very High	394.544	12.751

Given that the seven FIGUSED parameters are each scored on the 2–10 rank scale used throughout Table 6 and that the corresponding AHP weights (Table 5) sum to unity, the theoretical range of the FHIS score is bounded by [2.00, 10.00]. The upper bound of the Very High class reported above (10.00) reflects this theoretical maximum.

The Elevation (E) ranks reflect the basin's water-accumulation dynamics: the low-lying classes (22–38 m, 38–51 m) receive the highest susceptibility ranks (10, 8), consistent with their role as the basin's water-accumulation depressions described in Section 5.1.6, while the highest classes (62–72 m, 72–96 m) receive the lowest ranks (4, 2), reflecting their more effective natural drainage.

Similarly, under the Land Use (U) parameter, dense vegetation cover, which intercepts rainfall and favours infiltration as noted in Section 5.1.4, receives a lower susceptibility rank (6) than sealed built-up surfaces (8), which accelerate runoff.

The Slope (S) ranks follow a monotonic relationship, decreasing from the flattest class (0–1°, rank 10) to the steepest class (5–34°, rank 2): susceptibility is highest where the near-absence of gradient favours water stagnation, consistent with the abstract's description of gentle slopes as a factor exacerbating susceptibility, and with the same logic applied to the Elevation parameter above.

Table 7. Analytical upper bound on the shift in the FHIS score under $\pm 10\%$ and $\pm 20\%$ variation of each dominant parameter's weight (E, S, D), derived from the weights in Table 5 and the 2–10 parameter scoring scale of Table 6

Parameter	Weight (Table 5)	Δw at $\pm 10\%$	Δw at $\pm 20\%$	Max Δ FHIS at $\pm 10\%$	Max Δ FHIS at $\pm 20\%$
E (Elevation)	31.45%	3.15 pts	6.29 pts	0.25	0.50
S (Slope)	19.77%	1.98 pts	3.95 pts	0.16	0.32
D (Drainage Distance)	19.77%	1.98 pts	3.95 pts	0.16	0.32

Even under the most severe scenario considered (Elevation weight varied by $\pm 20\%$), the maximum possible shift in the FHIS score (0.50) remains well below the narrowest class interval in the model's five-class classification (1.18, for the Moderate class, Table 6). This analytical bound, obtained without requiring a full re-simulation of the weighted overlay, implies that only pixels whose FHIS score already lies within 0.50 of a class boundary could theoretically cross that boundary under the $\pm 10\%/\pm 20\%$ weight perturbations tested; pixels situated more than 0.50 from any boundary cannot change class. Table 7 therefore does not establish that the spatial ranking of susceptibility zones remains rigorously unchanged overall, but bounds the potential change to a narrow transitional fringe along class boundaries rather than to wholesale shifts of entire zones; a full re-simulation of the weighted overlay under each perturbation scenario would still be required to quantify precisely the share of the mapped area actually affected. Framed

in terms of spatial extent, pixels situated well within the interior of a class, which constitute the large majority of the mapped area given that class widths range from 1.18 to 2.93 (Table 6), remain unaffected regardless of the exact configuration of expert weights.

4.6. Results Validation

The results obtained from the FIGUSED method are subsequently validated against field data or previous flood cases to assess forecast accuracy and adjust the model as necessary [23].

Concretely, the approach consisted of compiling an inventory of confirmed flood points from field surveys, testimonies from riverside populations, and SODAGRI agents, then overlaying it on the FHIS map to assess the relative positions of these points within the model's susceptibility classes. In the absence of an inventory sufficiently georeferenced to compute a quantitative success rate (Success Rate Curve) or an AUC index, a limitation shown in the Discussion, this comparison was carried out qualitatively. The results of this comparison are presented and interpreted in Section (Validation).

5. Results

Table 6 presents the parameter values used in the FIGUSED method, as well as those related to flood susceptibility. The classes of each parameter are cross-tabulated with the areas (km²) and relative shares (%) they occupy in the basin, directly linking the weighting derived from the AHP matrix (Table 5) to the actual spatial footprint of each factor. The three sub-sections that follow present these results in increasing order of synthesis: the spatial distribution of each of the seven FIGUSED parameters taken individually, the resulting composite flood-susceptibility map obtained by overlaying them, and the validation of this map against historical flood records.

5.1. Analysis of the Parameters Used in the FIGUSED Method

The synthetic analysis of the seven FIGUSED parameters reveals that flood susceptibility in the Kayanga-Anambé basin stems from a strict multifactorial determinism, in which the geomorphological configuration structures the hazard, anthropisation exacerbates it, and hydro-climatic forcing triggers it.

At the morpho-topographic level, the near-total flatness of the relief, with 52.82% of slopes below 1° combined with the low elevations of the central basin (E), annihilates the gravitational energy needed to evacuate water. This deficit in natural drainage produces prolonged stagnation, particularly acute along flow-accumulation convergence axes (F) and in the immediate vicinity of the hydrographic network (D), where 49.74% of the territory lies within 4 km of watercourses.

This physical constraint is amplified by pedo-lithological and anthropogenic components: the alluvial sedimentary substrate (G), covering 93.00% of the area, offers low permeability once saturated, while SODAGRI's hydro-agricultural developments land use (U) with 25.37% cropland and the expansion of built-up areas (17.14%) seal surfaces, reduce hydraulic roughness, and push the effective runoff coefficient toward unity by mid-rainy season. Finally, rainfall intensity (I) acts as the dynamic trigger factor: under the impulse of Sudano-Guinean rainfall extremes, with 53.45% of the basin receiving more than 958 mm, massive volumes of water are injected into an already physically and topographically saturated environment, causing the network to overflow irreversibly and submerge agricultural perimeters.

5.1.1. Flow Accumulation

The Kayanga-Anambé basin exhibits a binary configuration: 99.65% of the surface (3115.17 km²) shows low accumulation, while critical zones (scores 8 and 10) are spatially very restricted (<0.1%). This extreme concentration precisely locates the points of hydrographic convergence where flow energy is at its maximum. These sectors, although minimal in area, are the strategic nodes where major overflows are

triggered. They constitute the natural outlets where hydraulic pressure systematically exceeds the storage capacity of the minor bed, causing flooding through slope-break or confluence effects (Figure 3).

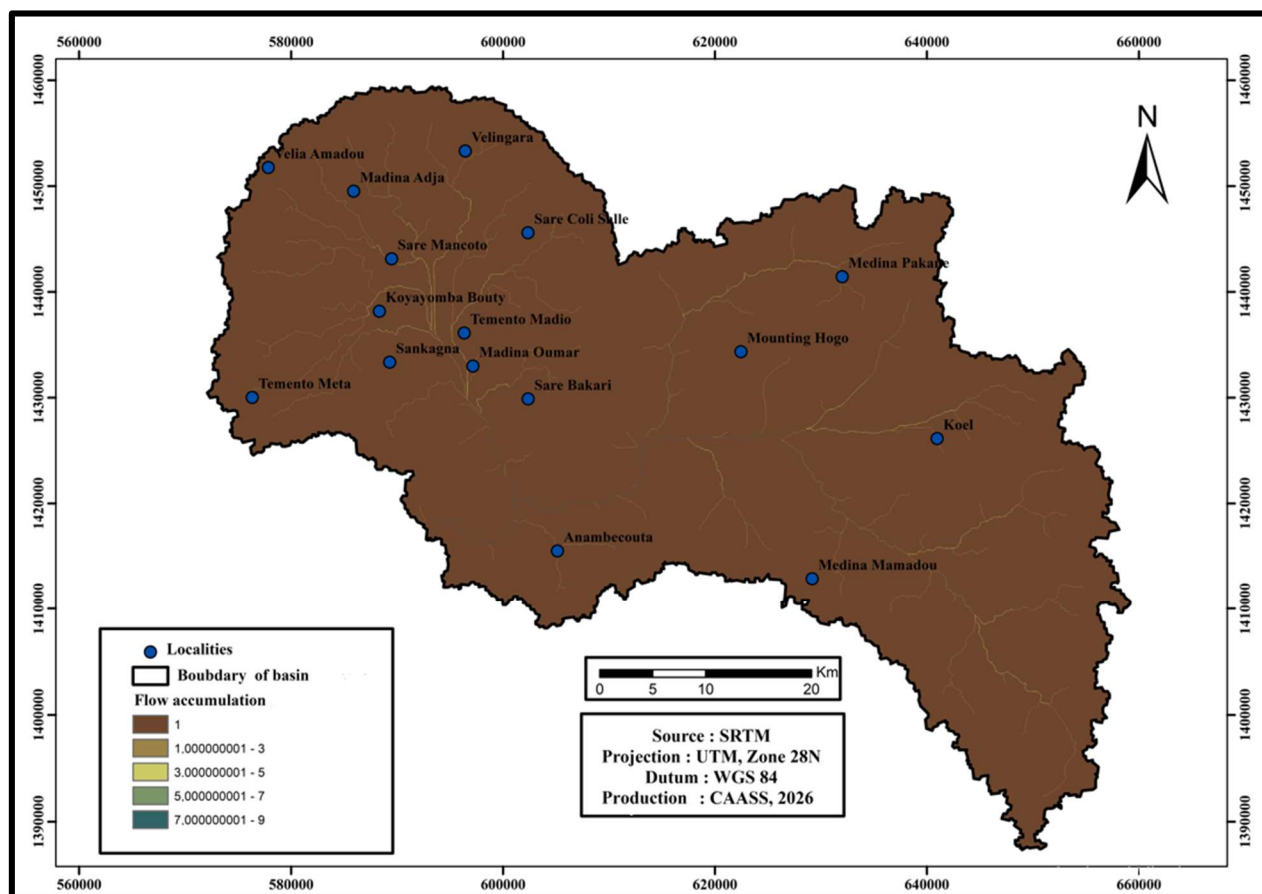


Figure 3. Values of the Flow Accumulation parameter.

5.1.2. Rainfall Intensity

Climatic hazard shows increasing severity toward the south: more than 53% of the basin experiences rainfall exceeding 958 mm (classes 6–10). Score-10 class (>1049 mm), although limited to 7.9% of the territory, represents the main driver of surface runoff. This spatial distribution shows that nearly half of the basin is exposed to intensities capable of instantly saturating soils. The precipitated water volume, coupled with the temporal concentration of the monsoon, imposes a hydric load that SODAGRI's developments must absorb or risk submersion (Figure 4).

5.1.3. Geology

Lithology is dominated (93%) by the Cretaceous-Quaternary sedimentary complex (class 2), lending a certain uniformity to the basin's surface permeability. However, the presence of the Hercynian orogen (score 10) and Cambrian sedimentary rock over roughly 4% of the area creates zones of preferential runoff. These older and often denser formations favour rapid water transfer toward the hydrographic network. The homogeneity of the sedimentary basin facilitates modelling, but the rare metamorphic zones act as flow accelerators, warranting upstream monitoring (Figure 5).

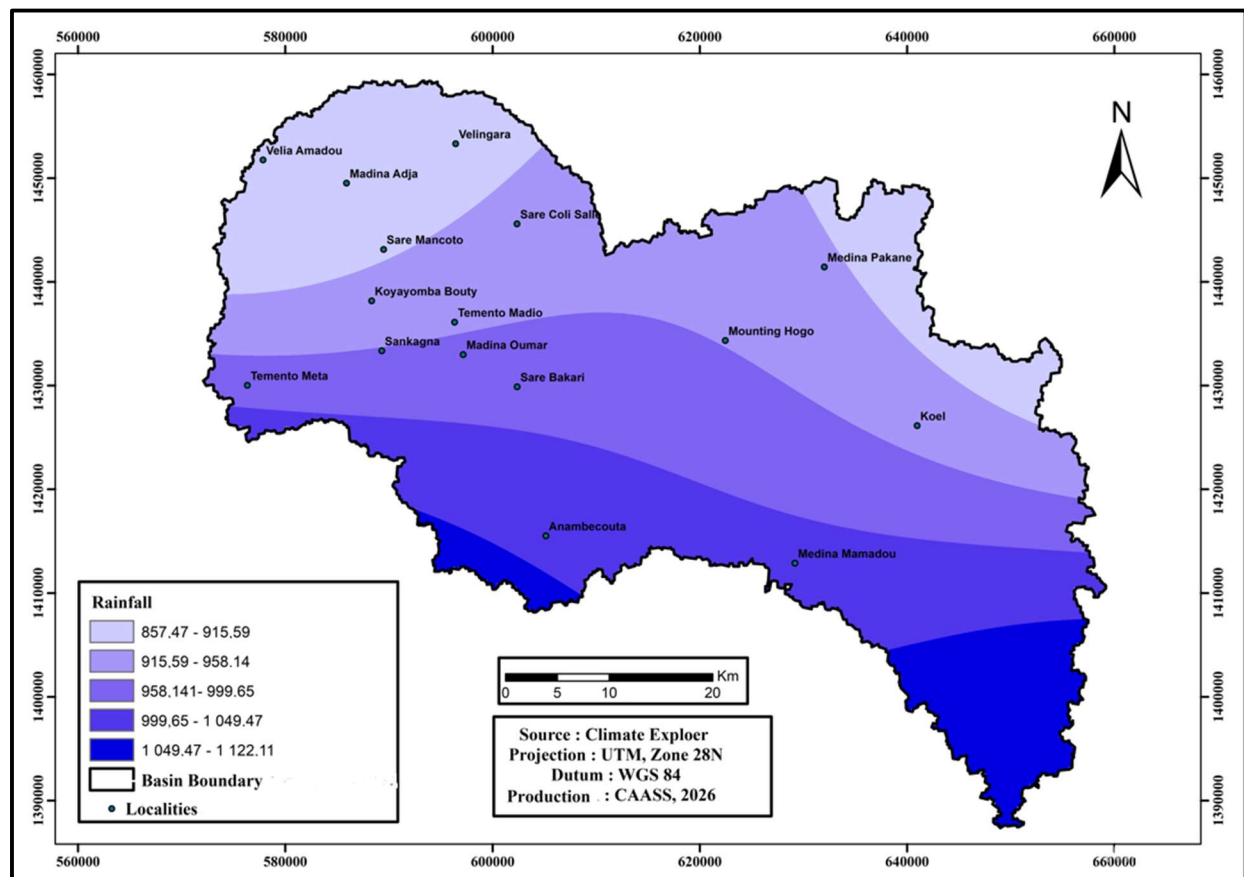


Figure 4. Values of the Rainfall parameter in the Kayanga-Anambé basin.

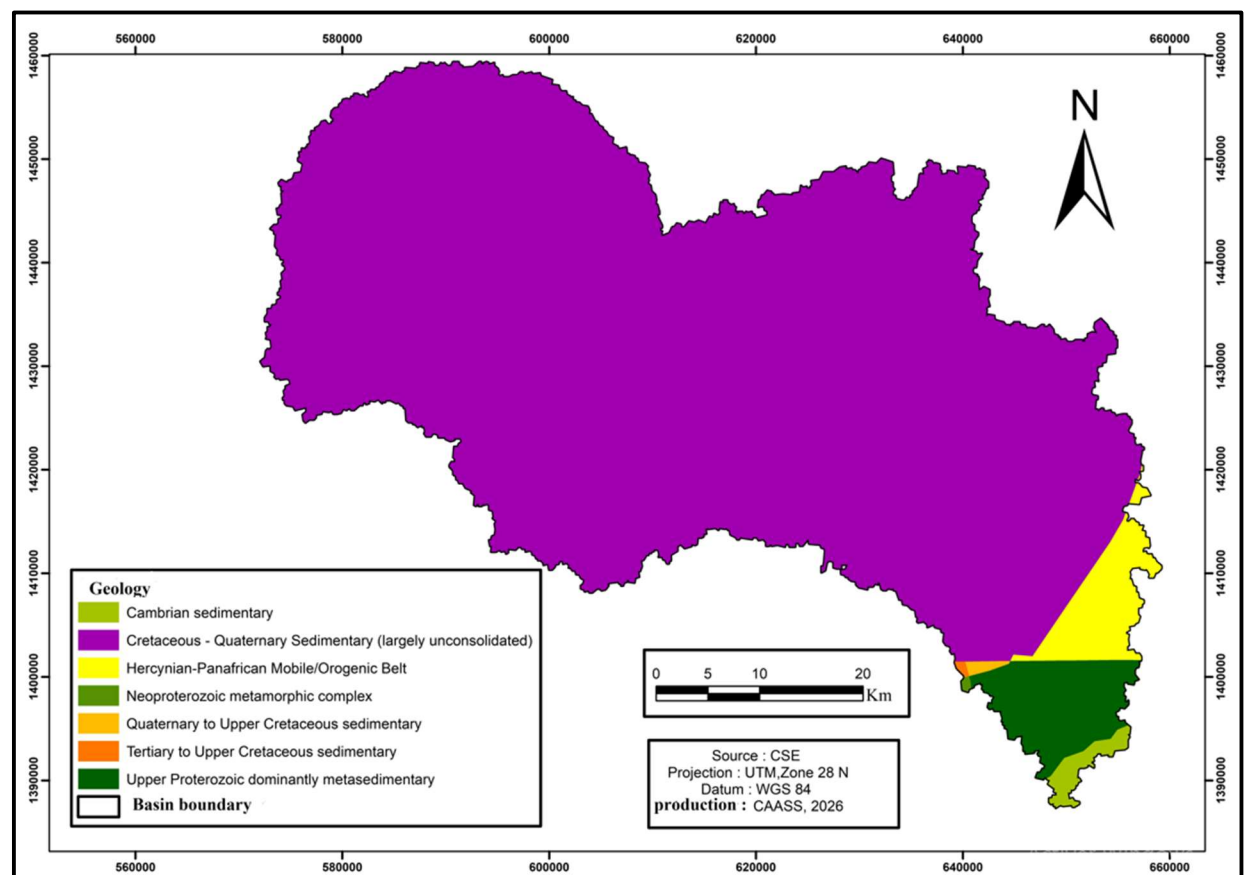


Figure 5. Values of the Geology parameter in the Kayanga-Anambé basin.

5.1.4. Land Use

Vegetation cover remains predominant (52.86%), providing a non-negligible ecosystem service of runoff attenuation. However, anthropogenic pressure is strong, with 25.3% cropland and 17.1% built-up surfaces. The critical point lies in bare soils (score 10): although they represent only 1.3% of the basin, their maximal runoff coefficient sharply accelerates the hydrological response. The progressive replacement of vegetation by extensive cropland reduces interception and infiltration, increasing the vulnerability of rice perimeters located downstream of these transfer zones (Figure 6).

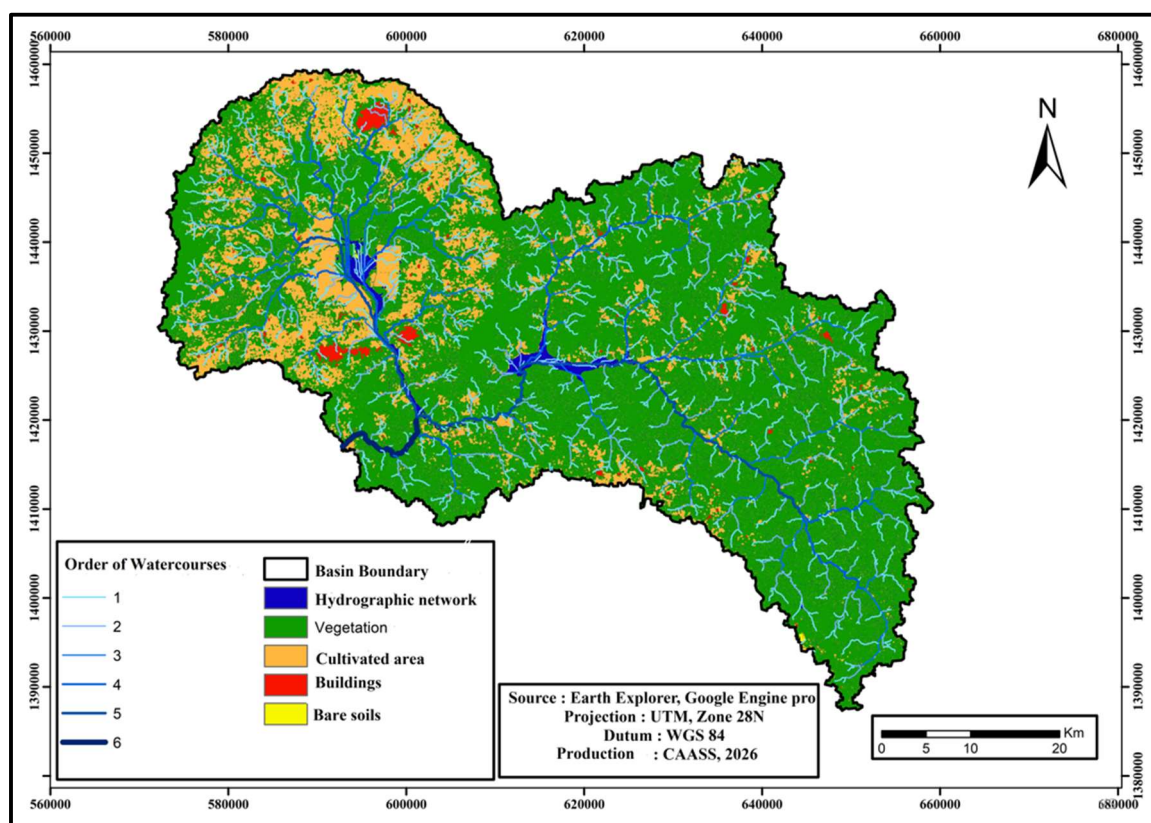


Figure 6. Values of the “Land Use” parameter in the Kayanga-Anambé basin.

5.1.5. Slope

Topography is the major factor of structural aggravation: 52.82% of the basin presents a near-zero slope ($0\text{--}1^\circ$), classified with the maximum score of 10 (Table 2). This widespread flatness explains the prolonged stagnation of water in the Anambé basin. Conversely, steep slopes ($5\text{--}34^\circ$) cover only 1.69% of the surface, acting as rapid runoff initiation zones. The basin’s configuration therefore favours slow but massive accumulation of water in low-lying areas, where the absence of slope prevents any natural gravity-driven evacuation, making floods particularly persistent after peak events. Indeed, Slope (S) and Drainage Distance (D) are, after Elevation, the second most heavily weighted parameters in the AHP matrix (19.77% each, Table 5), statistically confirming their structuring role in the FHIS index (Figure 7).

5.1.6. Elevation

The basin is divided into two domains: low-lying zones (scores 8 and 10), covering 34.5% of the area, and plateau zones (scores 2 and 4), representing 42.6% (Table 2). This altimetric distribution creates a permanent vertical transfer gradient. Low-elevation areas (22–38 m) receive by gravity the entirety of runoff water from the surrounding plateaus (Figure 8). The FIGUSED model identifies these low-altitude areas as temporary storage receptacles. Risk management here depends on the capacity of the infrastructure

to evacuate flows from high-elevation sectors toward the basin outlet. This predominant role is corroborated by the AHP weighting matrix (Table 5), which assigns Elevation (E) the highest weight among the seven parameters (31.45%).

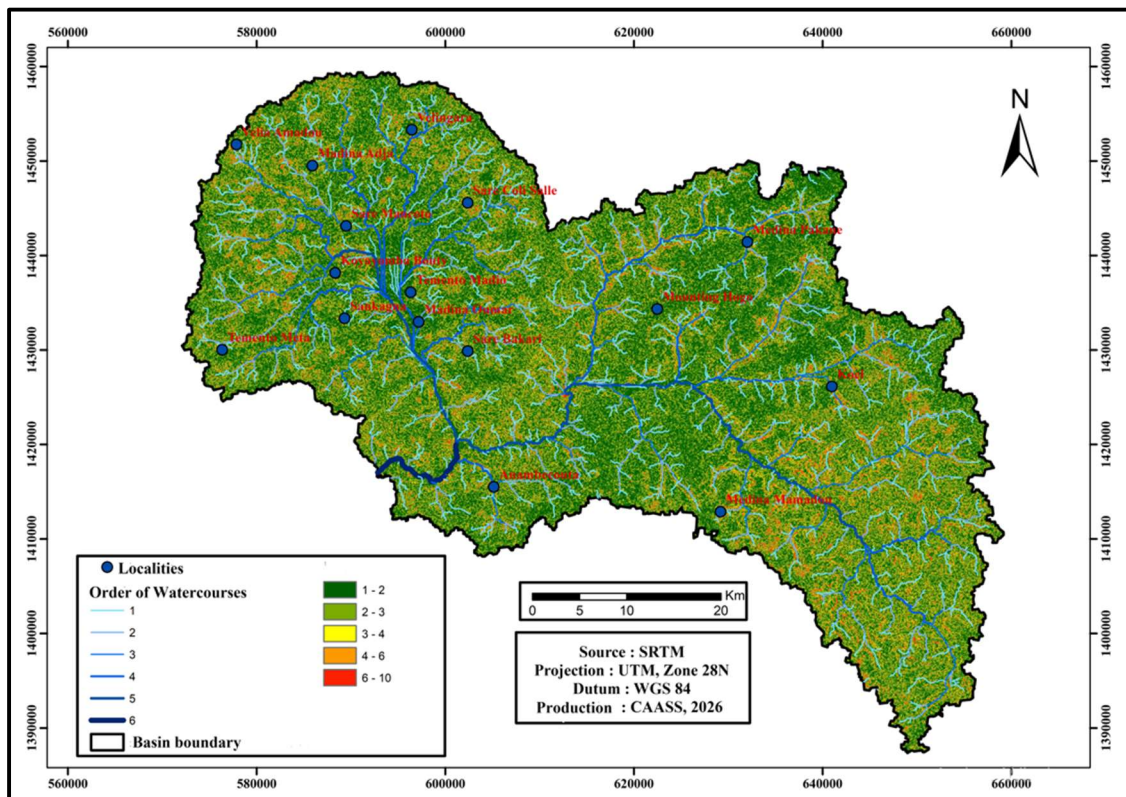


Figure 7. Values of the Slope parameter in the Kayanga-Anambé basin.

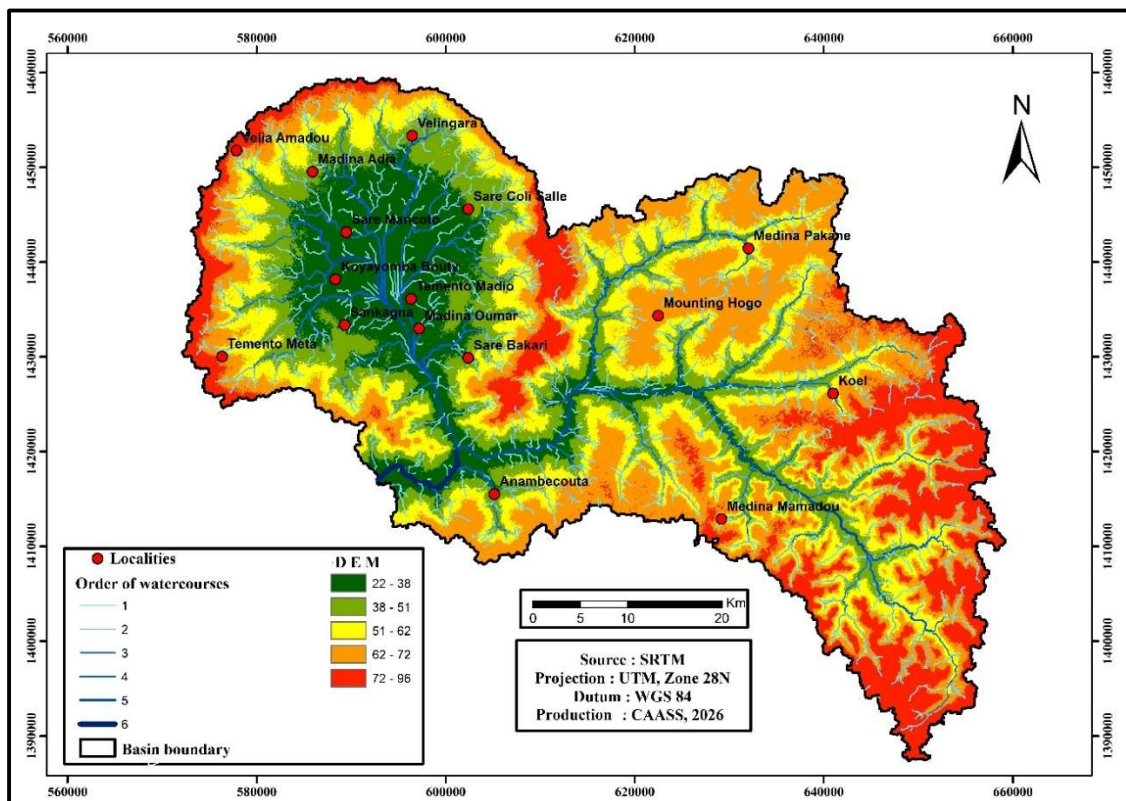


Figure 8. Values of the Elevation parameter in the Kayanga-Anambé basin.

5.1.7. Distance to Drainage

Proximity to the hydrographic network is a critical exposure factor. Nearly 50% of the basin (score 10) lies in the immediate vicinity of drainage axes. This pervasiveness of the network indicates that most of the territory is vulnerable to lateral overflow from the Kayanga and the Anambé. Only a tiny fraction of the basin (0.14%) is truly distant from watercourses (Table 2). This shows that flood hazard is not localised but widespread across the entire alluvial plain, making any human or agricultural installation within 4 km of drainage potentially dangerous (Figure 9).

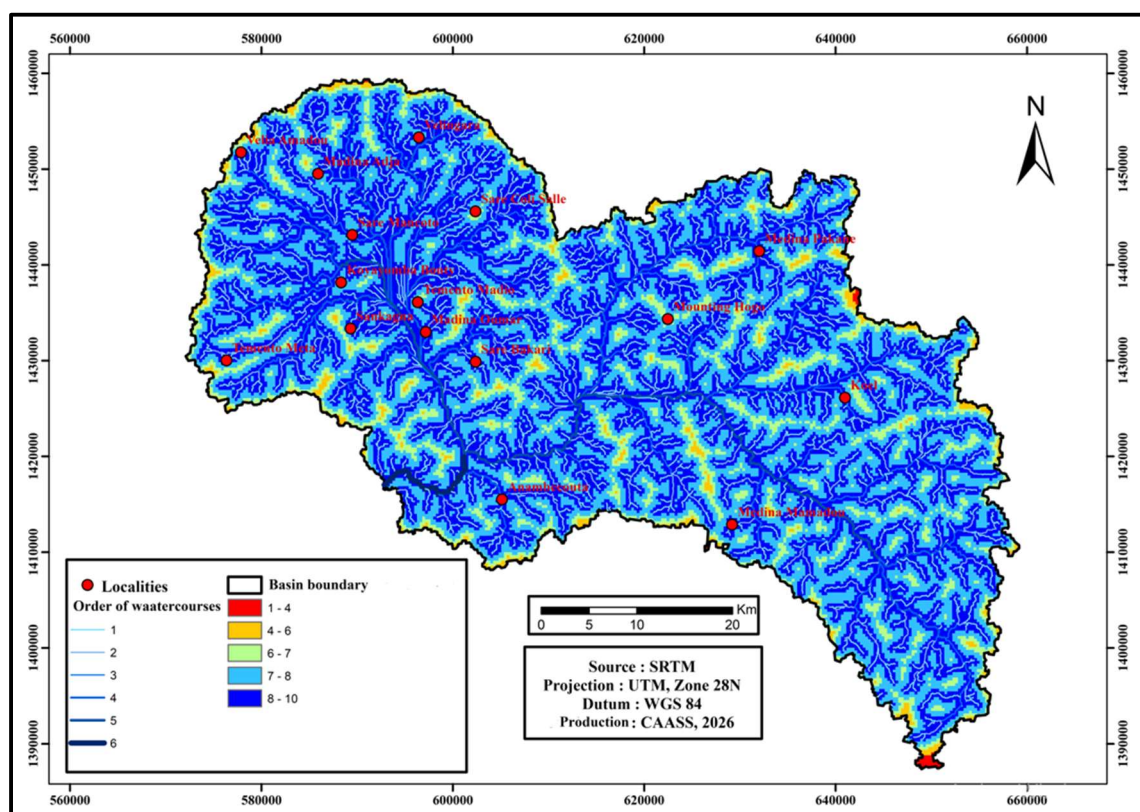


Figure 9. Values of the Euclidean Distance parameter in the Kayanga-Anambé basin.

5.2. FIGUSED Flood Susceptibility

Analysis of the flood-susceptibility index in the Kayanga-Anambé basin, generated by the FIGUSED model, makes it possible to spatialise the susceptibility of this strategic agricultural hub (Figure 10). Unlike in urban contexts, susceptibility here is dictated by rural morphometry and hydro-agricultural developments, chiefly those of SODAGRI.

The various susceptibility classes are distributed as follows:

- ❖ Very Low Susceptibility (475.88 km², that is 15.38%): This category corresponds to plateau areas and interfluvies distant from the drainage network. These regions, located on high points, are naturally protected by gravity, which facilitates rapid downstream water evacuation.
- ❖ Low Susceptibility (571.41 km², that is 18.47%): These areas show limited susceptibility, often located on moderate slopes. Although little exposed to Kayanga overflows, they may experience diffuse runoff during extreme rainfall events exceeding 1000 mm/year.
- ❖ Moderate Susceptibility (789.53 km², that is 25.52%): Constituting an important buffer zone, this class covers transition areas between the plateaus and the alluvial plain. It requires particular attention, as the rainfall intensification observed in the climatic data (score classes 8 and 10) can saturate these soils and increase the runoff coefficient toward the basin.

- ❖ High Susceptibility (862.92 km², that is 27.89%): This is the dominant class in terms of area. It encompasses low-relief zones and agricultural perimeters located near the hydrographic network. Here, the gentle slope (0–1°) prevents effective natural drainage, making these areas extremely dependent on existing channelling infrastructure.
- ❖ Very High Susceptibility (394.54 km² that is 12.75%): These are the most critical areas of the basin. They are located in the Anambé basin, at confluences and sectors of minimal elevation (22–38 m). In these “score 10” zones for flow accumulation, submersion is almost systematic during Kayanga flood peaks, directly threatening rice production.

Figure 11 restates the class breakdown mapped in Figure 10 as relative shares of the total basin area, making explicit that the combined High and Very High classes (40.64%) already exceed the Moderate class alone, which is the basis for the “heightened overall susceptibility” reading given in the abstract and discussed further in Section 6.

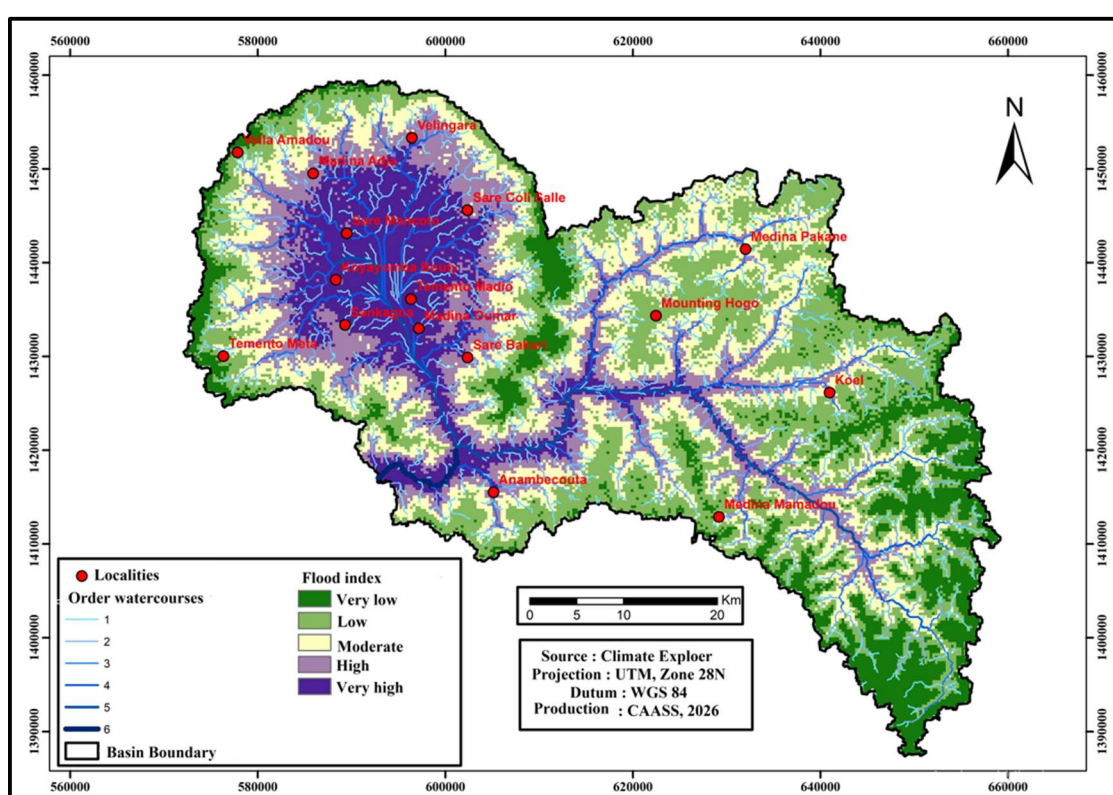


Figure 10. Flood Susceptibility Indices in the Kayanga-Anambé basin.

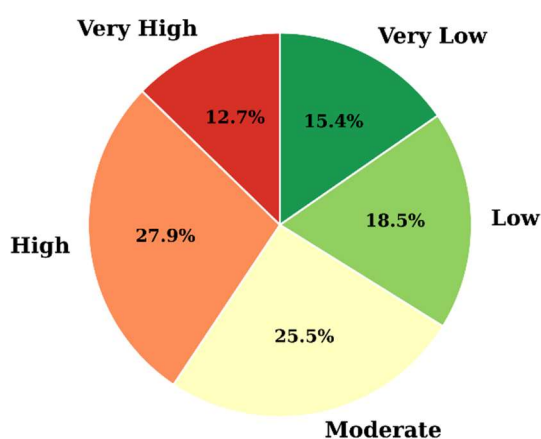


Figure 11. Percentage of susceptibility levels across the floodable area of the Kayanga-Anambé watershed.

5.3. Validation

The comparison between the FIGUSED susceptibility map and historical floods recorded in Haute-Casamance reveals a qualitative spatial concordance. Confluence zones and clay-rich depressions identified by the model coincide with sectors that suffered the heaviest damage in the past. However, increasing deforestation (noted in the Land Use parameter) suggests that previously stable areas could see their susceptibility level rise, requiring continuous updates to SODAGRI's management plans.

More precisely, this qualitative correlation was substantiated by overlaying the inventory of confirmed flood points onto the FHIS susceptibility-class map, without a quantitative success rate (percentage of correctly classified points, AUC index) being computable, owing to the lack of a sufficiently georeferenced validation-point inventory (see “Limitations of the Study” in the Discussion). This qualitative spatial agreement, combined with the stability of the susceptibility-zone ranking observed during the sensitivity analysis, offers a first level of confidence in the FHIS map as a decision-support tool for SODAGRI.

6. Discussion

The spatial analysis of flood susceptibility using the FIGUSED multi-criteria model demonstrates that the susceptibility of the Kayanga-Anambé basin stems from a mixed hydro-climatic and geomorphological determinism, in which the topographic configuration exacerbates anthropogenic pressures. Our results indicate that slope (S) is the major structural aggravating factor: 52.82% of the basin's area (that is 1644.86 km²) exhibits an extremely gentle gradient, between 0 and 1°. This near-total flatness, characteristic of the region's sedimentary deposition plains (the Cretaceous-Quaternary covering 93.00% of the basin's geology), corroborates the findings of [50] on the flat topography of Senegalese basins (Pikine and Keur Massar) as well as the observations of [51] in the Bafing basin. The absence of a hydraulic gradient annihilates the network's gravitational energy, neutralises natural evacuation capacities, and causes prolonged water stagnation, particularly in sectors located in the immediate vicinity of the drainage network, where 49.74% of the territory falls within a critical distance class (D: 1–4). In this context, the installation of developments or levees without rigorous consideration of flow-accumulation lines (F) ultimately disrupts natural flows and amplifies local submersion [52].

From a decision-making standpoint, this diagnosis calls for restrictive zoning: future hydro-agricultural developments must imperatively integrate the critical-slope map ($S < 1^\circ$) to avoid siting high-value perimeters within receiving topographic depressions.

At the same time, hazard continues to be fed by rainfall severity (I), with 53.45% of the basin's area recording high totals exceeding 958 mm (with 26.95% between 958–999 mm and 18.60% between 999–1049 mm). As ref. [3] noted in his analysis of floods in the Sahel, the concrete manifestation of risk and its social perception are closely tied to the redistribution of these rainfall flows through changes in surface conditions. In the Anambé basin, land use (U) acts as a critical catalyst: although vegetation still covers 52.86% of the basin, the significant presence of cropland (25.37%, that is 792.95 km²) and built-up surfaces (17.14%) accelerates direct runoff at the expense of infiltration. This process of hillslope anthropisation, documented by [53] in the Ouémé basin as a vector amplifying peak discharges, generates in our study area a genuine “structural vulnerability” characterised by an acute spatial mismatch between the spatial distribution of agricultural investments (SODAGRI rice plots) and the physical reality of submersion. Highlighting these friction zones through flood-potential indices [23] offers a direct operational lever for water governance.

Since FIGUSED characterises static spatial susceptibility rather than the dynamic regulatory effect of reservoir operations, it cannot by itself prescribe reservoir management rules; it can, however, delineate where such rules would have the greatest operational value. On one hand, a complementary avenue of future research would be to couple this susceptibility map with conceptual modelling of extreme flows, such as

the GR4J model tested by [53] in a data-scarce context, so as to design synchronised preventive releases from the Niandouba and Confluent dams ahead of monsoon peaks. On the other hand, SODAGRI must adjust the cropping calendar to prevent the rice maturation phase from coinciding with statistical windows of peak rainfall.

It should also be stressed that downstream flood susceptibility is not governed by dam releases alone: rainfall is markedly higher upstream than downstream of the dams, yet a substantial volume of water still reaches the downstream reaches independently of controlled releases, through local rainfall and uncontrolled tributary inflow that escape reservoir regulation altogether. This confirms that the static susceptibility diagnosis produced by FIGUSED retains direct operational relevance downstream of the dams, regardless of how reservoir operations are eventually optimised.

These results must nevertheless be interpreted in light of several methodological limitations. First, the resolution of the SRTM DEM (30 m) remains insufficient to finely discretise the micro-relief of such a flat basin, where sub-metre altimetric variations nonetheless govern the actual direction of flow; a higher-resolution DEM (LiDAR or drone-based) would help refine the delineation of convergence axes. Second, although the sensitivity analysis confirmed the relative stability of the susceptibility-zone ranking under variation of the AHP weights, the weighting remains fundamentally dependent on the judgment of the experts consulted and could evolve with a larger panel. Furthermore, the FIGUSED model, being static and index-based in nature, captures neither the temporal dynamics of floods (duration, rate of water rise) nor the variable regulatory effect of the Niandouba and Confluent dams depending on their fill level, which limits its scope to a susceptibility map rather than an operational flood forecast. Finally, the absence of prospective climate-change scenarios or land-use evolution restricts the validity of the conclusions to the temporal horizon of the data used (CHIRPS 1981–2025, Sentinel-2). Lastly, for lack of a georeferenced inventory of confirmed flood points, model validation rests on a qualitative comparison with known historical floods rather than on a quantified statistical indicator (success rate, AUC index); building such a field inventory is a priority for future quantitative validation of the model. Another limitation concerns the Rainfall (I) parameter of the FIGUSED acronym: in the absence of sub-daily precipitation records for the basin, I was operationalised as the mean annual rainfall total rather than a true short-duration rainfall intensity; it therefore captures the overall pluviometric load and progressive soil saturation rather than the triggering effect of intense short-duration storms, which future work with higher-frequency rainfall data could usefully complement. A further methodological limitation concerns the Flow Accumulation (F) parameter: the exact numerical thresholds of the five classes reported in Table 4, obtained via Jenks Natural Breaks on the raw output of ArcGIS 10.8's Flow Accumulation tool, could not be retrieved from the original GIS project; the class boundaries should therefore be understood as ordinal breakpoints identified by the classification algorithm for this basin, rather than as upstream-cell values directly interpretable in a given unit. A further limitation concerns the potential redundancy among the four parameters derived, directly or indirectly, from the same SRTM DEM (Elevation, Slope, Flow Accumulation, and Distance to Drainage), which together carry 82.47% of the total AHP weight (Table 5). Because these parameters are computed sequentially within the same hydrological model (flow direction, accumulation, and drainage distance are all derivatives of elevation), they necessarily share spatial structure, which could lead the topographic signal to be counted more than once in the FHIS score. This risk is partly mitigated by the fact that each parameter captures a functionally distinct aspect of topographic control on flooding (absolute elevation, local steepness, upstream contributing area, and proximity to the drainage network), and the sensitivity analysis (Table 7) shows that even a $\pm 20\%$ perturbation of the two most heavily weighted of these parameters, Elevation and, by extension, the correlated Slope and Distance layers, cannot shift any pixel across a susceptibility-class boundary. Nonetheless, a formal multicollinearity diagnostic (e.g., Variance Inflation Factor) between DEM-derived layers was not performed in this study and is recommended for future applications of the FIGUSED framework. An additional limitation concerns the spatial harmonisation of

the seven parameter layers: the individual F, I, G, U, S, E, and D rasters, prior to their final clipping, cover a slightly larger extent (approximately 3126 km²) than the basin mask used to derive the final FHIS susceptibility map (approximately 3094 km², consistent with the 3095 km² basin area reported in Section 3), a discrepancy of about 1% attributable to imperfect harmonisation of the raster extents at the pre-processing stage. While this does not affect the relative pattern of susceptibility described in Section 5, future applications of the method should verify that all input layers are clipped to an identical basin mask before the weighted overlay is computed. These limitations open avenues for further research rather than undermining the operational relevance of the spatial diagnosis produced.

Ultimately, the overall result of the FIGUSED model reveals that 40.64% of the basin's area presents high (27.89%, that is 862.92 km²) to very high (12.75%, that is 394.54 km²) susceptibility, against 25.52% moderate susceptibility and 33.85% low to very low susceptibility. This spatial distribution calls for a paradigm shift in public civil protection and rural land-use policy in Haute-Casamance. The immediate integration of this mapping into a community-based Early Warning System (EWS), in line with the recommendations of [54] for disaster-risk reduction in West Africa, is an essential condition for safeguarding public investment. To support this low-cost spatial monitoring, the territorial administration should modernise its tools by adopting the coupling of radar satellite remote sensing with cloud computing via the Google Earth Engine (GEE) platform, whose effectiveness for near-real-time operational monitoring of floodable areas was demonstrated by [55]. By converting these modelled results into decision-support tools, Senegalese authorities will have the levers needed to durably secure rice production and strengthen the resilience of the basin's rural communities in the face of climatic change.

7. Conclusions

The assessment of flood susceptibility in the Kayanga-Anambé watershed, carried out by coupling the FIGUSED model with Spatial Multi-Criteria Analysis (AHP-GIS), has produced a spatially detailed diagnosis of the spatial distribution of hydro-climatic susceptibility in this strategic territory of Haute-Casamance. The modelling results reveal major physical susceptibility: 40.64% of the basin's total area (that is 1257.47 km²) exhibits "High" (27.89%) to "Very High" (12.75%) susceptibility. This configuration is not simply the product of rainfall hazard. However, it stems from a critical synergy between an extremely flat topography, characterised by slopes below 1° over 52.82% of the territory, and a very dense drainage network, in which 49.74% of the surface lies in the immediate vicinity of flow axes, directly exposing SODAGRI's rice perimeters to recurrent submersion. The expansion of cropland (25.37%) and built-up areas (17.14%) accelerates direct runoff, confirming that anthropisation exacerbates the basin's response time during late-monsoon rainfall extremes.

Nevertheless, the scope of these results must be assessed in light of certain methodological limitations. On one hand, the spatial resolution of the Digital Elevation Models used (SRTM 30 m) remains limited for capturing fine topographic micro-relief and the precise geometry of artificial drainage channels. On the other hand, the AHP method retains an inherent degree of subjectivity in setting pairwise comparison weights, while the lack of continuous *in-situ* gauging stations limits temporal hydraulic validation to empirical field-based approaches.

In light of these findings, several operational recommendations are warranted for territorial management:

- ❖ Restrictive agricultural zoning: Integrate the FIGUSED susceptibility map into SODAGRI's Master Development Plan to steer new investment away from the 40.64% of high-susceptibility zones.
- ❖ Governance of hydraulic infrastructure: complement this static susceptibility diagnosis with dynamic reservoir-operation modelling to synchronise the management of the Niandouba and Confluent dams through calibrated preventive releases ahead of monsoon peaks.

- ❖ Establishment of an Early Warning System (EWS): Deploy automated water-level sensors in “Very High” susceptibility sectors to warn rural communities and adjust planting calendars.

The stability of the susceptibility-zone ranking confirmed by the sensitivity analysis and its agreement with observed historical floods gives these three recommendations a sufficient operational basis to begin implementation now, through SODAGRI and the State’s decentralised technical services, without waiting for further hydrometric validation.

Finally, this work opens new research perspectives. Future studies would benefit from coupling the FIGUSED index model with 2D hydraulic-hydrodynamic models (such as HEC-RAS 2D or TELEMAC) that are fed by very high-resolution DEMs (from drone or LiDAR data) to simulate water depth and flow velocity. Moreover, integrating Cloud Computing via Google Earth Engine (GEE) and using Sentinel-1 radar imagery will make it possible to develop near-real-time satellite monitoring of flood extents, strengthening the basin’s resilience to future climatic change.

Beyond the case of the Kayanga-Anambé, the regionalisation approach to the FIGUSED model proposed here coupling an AHP-GIS multi-criteria index with open remote-sensing data in a context of scarce gauging is transferable to other flat, strongly anthropised hydro-agricultural basins in West Africa (irrigated perimeters of the Senegal, Gambia, or Volta rivers), as well as to other sectors facing similar rural water-management challenges, such as agricultural land-use planning, index-based climate-risk insurance, and rural infrastructure planning. It therefore constitutes a methodological contribution that extends beyond the sole scope of the case study presented.

Statement of the Use of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this manuscript, the authors used Google Gemini in order to assist with cartographic tasks. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Author Contributions

Conceptualization, C.A.A.S.S. and B.S.; Methodology, C.A.A.S.S. and B.S.; Software, C.A.A.S.S.; Validation, C.A.A.S.S. and B.S.; Formal Analysis, C.A.A.S.S.; Investigation, C.A.A.S.S.; Resources, C.A.A.S.S.; Data Curation, C.A.A.S.S. and Y.S.; Writing-Original Draft Preparation, C.A.A.S.S.; Writing-Review & Editing, C.A.A.S.S. Visualization, C.A.A.S.S. and Y.S.; Supervision, B.S.; Project Administration, Y.S.

Ethics Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The elevation data used in this study are from the SRTM (NASA/USGS); the geology data are from the British Geological Survey’s Africa Groundwater Atlas; the rainfall data are from Climate Explorer (CHIRPS); and the land use data are from Sentinel-2 imagery accessed via Google Earth Engine.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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