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Flood Risk Assessment in the Lower Valley of Ouémé, Benin

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Abstract

In response to the increased frequency of flood events in recent years, it has become crucial to enhance preparedness and anticipation through precise flood risk assessments. To this end, this study aims to produce updated and precise flood risk maps for the Lower Valley of Ouémé River Basin, located in the South of Benin. The methodology used consisted of a combination of geographical information systems (GIS) and multi-criteria analysis, including Analytical Hierarchy Process (AHP) methods to define and quantify criteria for flood risk assessment. Seven hydro-geomorphological indicators (elevation, rainfall, slope, distance from rivers, flow accumulation, soil type, and drainage density), four socio-economic vulnerability indicators (female population density, literacy rate, poverty index, and road network density), and two exposure indicators (population density and land use) were integrated to generate risk maps. The results indicate that approximately 21.5% of the Lower Valley is under high and very high flood risk, mainly in the south between Dangbo, So-Ava, and Aguégués. The study findings align with the historical flood pattern in the region, which confirms the suitability of the used method. The novelty of this work lies in its comprehensive approach, the incorporation of AHP for weighting factors, and the use of remote sensing data, GIS technology, and spatial analysis techniques which adds precision to the mapping process. This work advances the scientific understanding of flood risk assessment and offers practical insights and solutions for flood-prone regions. The detailed flood risk indicator maps obtained stand out from previous studies and provide valuable information for effective flood risk management and mitigation efforts in the Lower Valley of Ouémé.

Keywords

Flood, Hazard, Exposure, Vulnerability, Risk, Lower Valley of Ouémé

1. Introduction

Floods pose significant and recurrent threats as they are the most frequent, detrimental, and fatal natural disasters occurring globally on an annual basis [1]. They are the source of nearly half of all deaths from natural disasters over the past 50 years and are responsible for nearly one-third of global economic losses [1]. Multiple factors contribute to the occurrence of river flooding, including heavy rainfall in the upstream areas of rivers and modifications in land use, such as deforestation and urbanization. Excessive surface water runoff following heavy precipitation is the primary cause of river flooding [1]. With the increase in urbanization, the prevalence of impervious land surfaces also rises, leading to amplified rates of runoff. Additionally, saturated soils, high concentrations of suspended solids, and landslides further exacerbate the consequences of flooding. In developing nations, floods cause more significant harm and loss of life due to their elevated economic and human susceptibility [2]. According to the Office for the Coordination of Humanitarian Affairs (OCHA), floods have claimed victims in many West African countries [2].

Benin is severely affected by the negative consequences of global warming. It is one of the least developed nations, which also exhibit high susceptibility to the impacts of climate change due to their very limited resources as well as the development challenges and climate shocks. In September 2010, Benin was hit by torrential rains and floods. These events resulted in extensive harm to residences, educational institutions, healthcare facilities, transportation, commercial hubs, religious establishments, access to clean water, sanitation systems, and various communal resources and amenities [3]. All sub-sectors of the primary sector were affected by the floods. The agricultural sector was the most affected, with an estimated 50,764 ha of crops destroyed, as well as thousands of livestock deaths (drowning), and huge quantities of fish lost due to the destruction of fishing infrastructure. The flooding also caused the total or partial destruction of infrastructure and production equipment and stocks of raw materials and goods [3]. The lower valley of the Ouémé River Basin (LVO) serves as the basin's reservoir, characterized by a deltaic zone, where the majority of water accumulated from the upstream sections of the river is stored. The topography of this region exhibits minimal variations, featuring gradual slopes that facilitate the extensive dispersion and progression of floodwaters across vast floodplains. These floodplains hold significant potential for agricultural production. Nevertheless, the usage of this agricultural capacity remains inadequate, primarily influenced by the hydrological patterns of the river [4]. The LVO is witnessing climatic variability, which is becoming more and more pronounced, with a serious threat to the socio-economic conditions including the livelihoods of the riparian communities.

Flood zone mapping and event history play an important role in identifying flood zones, event intensity, flood depth, and the resulting harm it will inflict. Three primary methods exist for mapping flood-prone regions: a physical methodology, an empirical methodology, and physical modelling. The process of physical modelling involves conducting experiments to assess and verify the model's predictive capabilities [5]. Subsequently, a numerical model can be employed to simulate the flooding process across one, two, and three dimensions, enabling a comprehensive understanding of its dynamics [6], such as numerical models using Delft3D and HEC-RAS. The accuracy of flood prediction using the physical method necessitates numerous inputs, including morphological, topographic, hydrological, and remote sensing data that are processed within a Geographic Information System (GIS) [7]. The empirical method can be categorized into three models, specifically 1) multi-criteria assessment [8] [9]; 2) statistical techniques, encompassing both bivariate and multivariate models [10]; 3) models of machine learning and artificial intelligence [10] [11]. The empirical approach known as the Analytic Hierarchy Process (AHP) is the most commonly employed method for the multi-criteria analysis model [12]. The AHP approach is a process of assessing weights by comparing each parameter in pairs. These weights are then used to rank and evaluate the parameters, ultimately determining the optimal solution for a given problem [5] [13]. The combination of AHP method and GIS for flood analysis and floodplain mapping proves to be a dependable, effective, and precise approach that can be effortlessly implemented worldwide [8] [9]. This method's flexibility, ease of use, and affordability offer several benefits. These advantages enable its application in situations where detailed information is scarce, when generating extensive flood risk maps is the objective, or when policymakers need a quick assessment of flood risk. However, a disadvantage of the AHP approach lies in the determination of indicator weights, which rely on expert opinion. This assessment method is subjective and has cognitive limitations [14]. Nevertheless, this deficiency is mitigated by the assessment of ratio consistency. Satty (1980) concluded that to obtain a harmonious value between weighted factors, the ratio consistency threshold must be less than 10%.

Flood risk evaluation serves as the foundation for implementing measures aimed at minimizing the impact of floods. It enables decision-makers and managers to effectively safeguard the at-risk population and property by implementing strategies for flood prevention and mitigation. This study expands upon prior research by using a methodology that combines multi-criteria assessment techniques with the Geographic Information Systems (GIS) and the Analytic Hierarchy Process (AHP) to assess the effectiveness of risk and vulnerability management strategies concerning flooding in the Lower Valley of Ouémé. This research aimed to create a GIS-centered structure to map and evaluate the hazard, exposure, and vulnerability to floods in the Lower Valley of Ouémé. The method employed easily accessible data and simplified GIS analysis to assess flood hazards and vulnerability. The findings of this study will offer valuable information on the identification of flood-prone areas, enabling prompt measures for reducing flood risks.

2. Materials and Methods

2.1. Study Zone

The Ouémé's lower valley (**Figure 1**) is situated within the range of 6˚28' and 6˚56' in the Northern latitude, and between 2˚22' and 2˚35' in the Eastern longitude [15]. It extends over 1193 km^2 and is a vast topographic depression occupied by a plain that sinks downstream into the lagoon domain formed by the Lake Nokoué and Porto-Novo lagoon. The delta of Ouémé is a Ramsar site (1018). The area exhibits two primary morphological formations: specifically, the elevated plateau and the low-lying floodplain [16].

The Lower Ouémé Valley experiences a sub-equatorial weather pattern, consisting of two distinct dry seasons occurring from December to March and from August to September, as well as two rainy seasons spanning from April to July and from September to November.

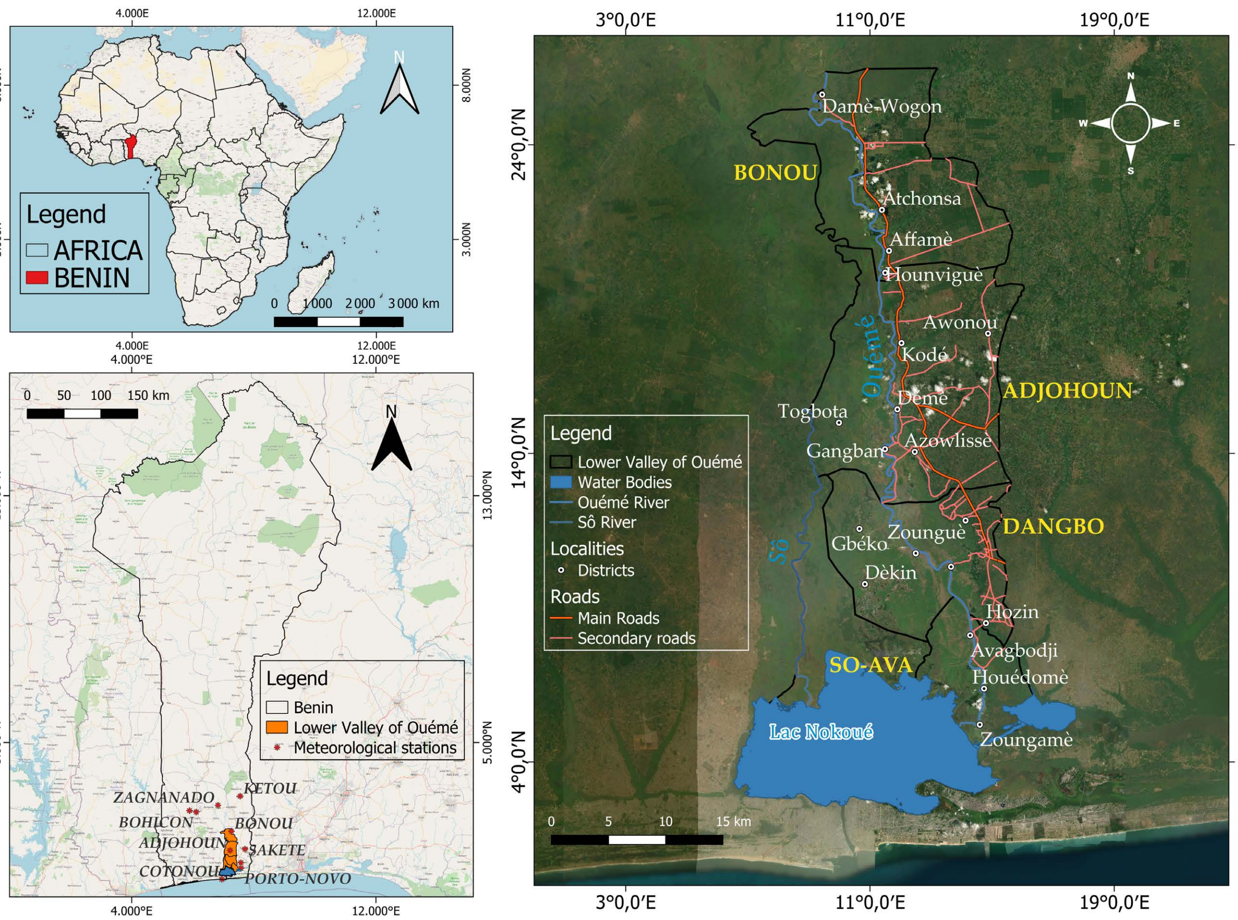

Figure 1. Study area's map location.

The average yearly temperature for the period (1971-2017) is 27˚C. Nevertheless, this value conceals notable variations in temperature extremes, with temperatures rising to over 30˚C in January-February (32˚C), and dropping below 26˚C in July-August (23˚C) [17]. The average annual rainfall is almost similar throughout the region, amounting to 1250 mm in Aguégués, Sô-Ava, and Dangbo and 1177 mm in Adjohoun.

2.2. Methodological Design

The methodology employed in this research involves a multi-criteria approach using GIS and AHP methods, for flood risk assessment by considering flood hazard, exposure, and socio-economic vulnerability. The flood hazard criteria rely on the parameters that have the greatest impact on river floods. Vulnerability assessment is based on identifying the most susceptible groups. Lastly, the exposure component is determined by analyzing the spatial layer of land use.

The research employs ArcMap (version 10.8) to generate, modify, and examine geospatial information. To accomplish this goal, we incorporated diverse datasets comprising remote sensing data, meteorological information obtained from weather stations, and additional auxiliary data. Daily precipitation data over 39 years (1981 to 2019) from 9 stations, 7 outside and 2 inside the study area were obtained from Météo Benin. A 30 m ground resolution digital elevation model (DEM) was acquired from the United States Geological Surveys (USGS) [18]. Population data were obtained based on census data of the 2013 General Census of Population and Housing (RGPH4) of Benin conducted by the National Institute of Statistics and Demography (INStaD) [19]. Soil information was acquired from the website of the Food and Agriculture Organization (FAO) [20]. Land-use maps [21] were extracted from the Sentinel-2 10 m global land use/land cover time series produced by Impact Observatory, Microsoft and Esri. This layer displays a global land use/land cover (LULC) map derived from ESA Sentinel-2 imagery at 10 m resolution; boundary and stream maps of the research region available on the IGN Benin website (National Geographic Institute of Benin) [22]; rate of literacy and poverty index [23] were also obtained on the Benin data portal website. Additional information, such as the way the public perceives flooding events, disasters, factors accountable for flooding, reasons behind flooding in the examined region, and the past occurrences of floods, was gathered via focus group discussions involving stakeholders, decision-makers, and local inhabitants, as well as through on-site surveys. The GPS equipment was used to acquire the geographical coordinates of areas that had experienced flooding incidents in the past. Furthermore, all the maps were assigned a reclassification scale ranging from 1 to 5, based on their level of influence on flood risk, with 1 indicating the lowest contribution and 5 representing the highest contribution.

2.3. Flood Risk Mapping

The predominant methods employed in Geographic Information Systems (GIS) for constructing flood risk assessment indicators involve either inductive or deductive approaches [24], the deductive methodology being selected for this study. The research took into account flood risk as the outcome, which is influenced by flood hazard, flood exposure, and socio-economic vulnerability. **Figure 2** illustrates the step-by-step process for generating the database, and the subsequent sections elucidate the approach undertaken for the different analyses.

2.3.1. Flood Hazards Indicators

When it comes to creating the flood hazard layer, there is a lack of agreement regarding the specific criteria that ought to be incorporated [25]. However, there are some factors considered in numerous studies that contribute to the vulnerability of an area to flooding [26] like elevation, slope, land use and distance from rivers. This analysis involved hydro-geomorphological elements [27] [28] [29], such as elevation, rainfall, soil type, slope, drainage density, flow accumulation, and distance from rivers as their impact affects flooding.

2.3.2. Flood Exposure Indicators

Physical exposure pertains to artificial infrastructure components that are susceptible to destruction caused by floods [30]. Economic loss is usually used to quantify the impact of physical damage. The necessary details to calculate it involve the value of the property, the type of structure, and its height. The land use and population density layers were used to assess the susceptibility of properties to economic losses.

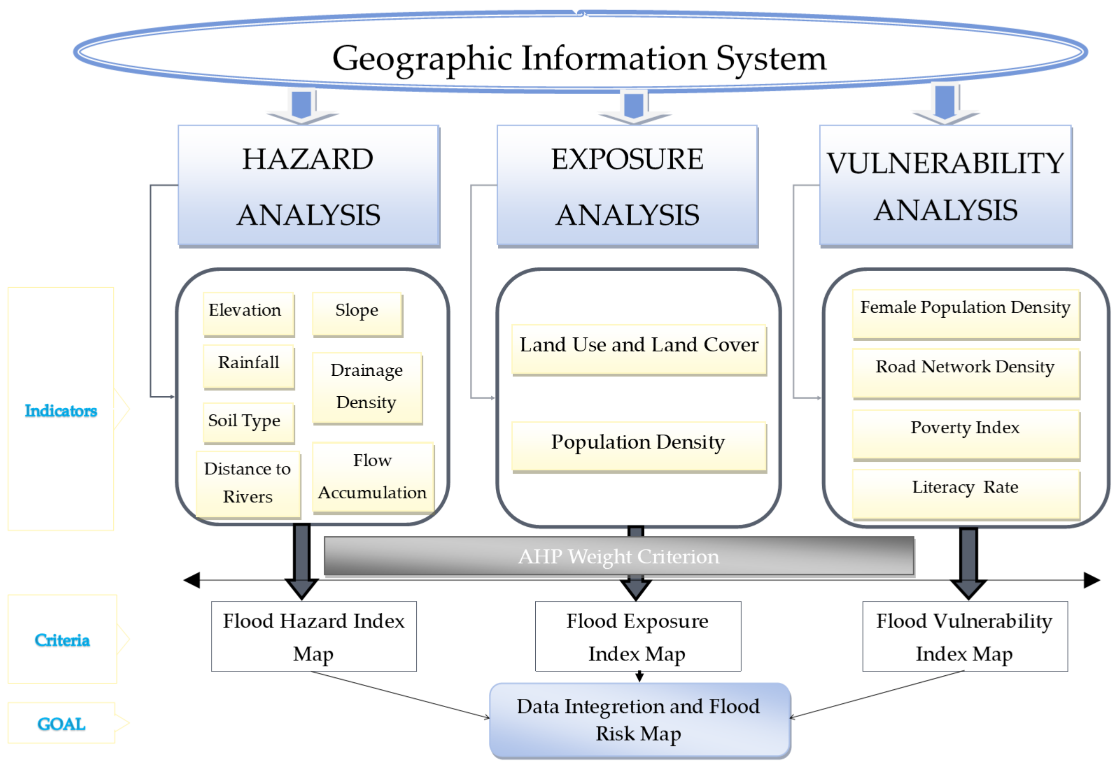

Figure 2. Flow chart showing methodological design for flood risk assessment with decision factor hierarchies.

2.3.3. Flood Vulnerability Indicators

Typically, evaluations of flood vulnerabilities consider the potential harm caused by a range of physical and socioeconomic factors, as well as the area and time-frame in question [31]. This research used and adjusted selected socio-economic vulnerability indicators [27] [32] [33] to fit the specific circumstances of the study region. The socio-economic measures chosen for this report include female population density, rate of literacy, poverty index and road network density.

2.4. Standardization of Indices for Evaluating Risks of Flooding

The UNDP's Human Development Index was used to finalize the normalization of indicators. Positive and negative functional connections with flood risk were established via Equations (1) and (2), correspondingly [24] [30].

$$N = 1 + 9 \times \frac{\left(V - V_{\min}\right)}{\left(V_{\max} - V_{\min}\right)} \tag{1}$$

$$N = 1 + 9 \times \frac{\left(V_{\max} - V\right)}{\left(V_{\max} - V_{\min}\right)} \tag{2}$$

V, $V_{\max}$ and $V_{\min}$ stand for the raw data, the minimum and the maximum of the raw data.

The normalization of indicators was carried out, with a scale range of 1 to 10, by taking into account the contribution of the variable to the components of flood risk.

2.5. Criteria Weight Determination through AHP

The Analytical Hierarchy Process (AHP), established by Saaty in 1990 [13], is a technique used in MCDM to assign weights to various criteria. This approach enables the comparison of two criteria by employing a pair-wise evaluation matrix, where relative importance values are assigned to indicate the preference of one criterion over another. It offers a quantification of consistent judgment backed by a theoretical framework. In this study, we used the AHP Excel Template Version 2018-09-15 developed by Klaus D. Goepel [34] to conduct pair-wise comparisons and perform calculations for determining weights and consistency rates (CR). The relative importance is measured on a standardized scale ranging from 1 to 9, where 1 indicates equal importance and 9 represents utmost significance. A quality assessment was conducted by evaluating the consistency ratio (CR), which assesses the reliability of the pairwise comparisons. This is necessary because real-life decision-making often involves some degree of vagueness, which can introduce inconsistencies in the matrix [27]. Consistency can only be achieved when the CR is below 0.10 [13] [35].

2.6. Development of the Index Measuring Flood Hazard, Exposure, and Vulnerability

The flood hazard index (HI), flood exposure (EI) and flood vulnerability index

(VI) were calculated by combining the assigned weights with the respective classes of hazard, exposure, and vulnerability at every level of the hierarchy, using Equations (3) through (6).

$$\mathrm{HI/VI/EI} = \sum_{i=1}^{n} W_i \times r_i \tag{3}$$

where "HI/EI/VI" is the Hazard/Exposure/Vulnerability, the weight of every indicator is represented by "Wi," while the rating of each indicator at each point is denoted as "r_i" "n" signifies the total count of criteria.

$$\mathrm{HI} = \mathrm{W_E} \times \mathrm{E} + \mathrm{W_{Sl}} \times \mathrm{Sl} + \mathrm{W_D} \times \mathrm{D} + \mathrm{W_S} \times \mathrm{S} + \mathrm{W_R} \times \mathrm{R} + \mathrm{W_F} \times \mathrm{F} + \mathrm{W_{DtR}} \times \mathrm{DtR} \tag{4}$$

where E; Sl; D; St; R; F; DtR are elevation, slope, drainage density, soil type, rainfall, flow accumulation, distance to rivers and W_E; W_{Sl}; W_D; W_S; W_R; W_F; and W_{DtR} represent their respective associated weights.

$$\mathrm{EI} = \mathrm{Lu} \times \mathrm{W_{Lu}} + \mathrm{P} \times \mathrm{W_P} \tag{5}$$

where Lu; P are land use, population density and $W_{Lu;}$ W_P their associated weights.

$$\mathrm{VI} = \mathrm{F} \times \mathrm{W_F} + \mathrm{R} \times \mathrm{W_R} + \mathrm{L} \times \mathrm{W_L} + \mathrm{IP} \times \mathrm{W_{IP}} \tag{6}$$

where F; R; L; IP are female density, road density, literacy rate, and poverty index and W_F; W_R; W_L; W_{IP} are their associated weights.

2.7. Index for Assessing Flood Risk

Flood risk can be expressed as the combination of three factors: "hazard," "exposure," and "vulnerability." By overlapping the spatial layers associated with the hazards Index (HI), exposure Index (EI), and overall vulnerability Index (VI), the flood risk indicator (RI) is computed for the designated region using Equation (7).

$$\mathrm{RI} = \mathrm{HI} \times \mathrm{EI} \times \mathrm{VI} \tag{7}$$

2.8. Validation of Flood Risk Map

The spatial risk maps were validated based on in-depth field investigation and document review. GPS equipment was used to collect the coordinates of various past flood locations [27] during fieldwork in February 2022. The lead author and field assistants conducted, recording of GPS coordinates for different areas that had experienced flooding in the past, including towns, villages, and farmlands. These coordinates were then plotted on the basin's flood risk map, enabling a comparison between observation data and modelled flood risk.

3. Results and Discussion

3.1. Flood Hazard Indicators

The flood hazard indicators considered and the corresponding comparison are listed in Table 1.

Table 1. Matrix comparing indicators of flood hazards.

Flood Hazard Indicators	Elevation	Slope	Rainfall	Drainage Density	Soil Type	Flow Accumulation	Distance from Rivers
Elevation	1.00	2.00	5.00	3.00	2.00	7.00	1.00
Slope	0.50	1.00	3.00	3.00	1.00	5.00	0.50
Rainfall	0.20	0.33	1.00	1.00	0.50	3.00	0.20
Drainage Density	0.33	0.33	1.00	1.00	1.00	3.00	0.25
Soil Type	0.50	1.00	2.00	1.00	1.00	3.00	0.33
Flow Accumulation	0.14	0.20	0.33	0.33	0.33	1.00	0.14
Distance from Rivers	1.00	2.00	5.00	4.00	3.00	7.00	1.00
Total	3.68	6.87	17.33	13.33	8.83	29	3.42

The altitude of a catchment area is among the elements that influence the potential for flooding in this region [35]. The valley reaches a peak of 140 m in elevation, with the lowest point located at −4 m relative to sea level. The category of the lowest elevation corresponds to a class with a designation of high flood risk, whereas the highest elevation falls under a class denoting low flood risk. It is shown in **Figure 3(a)** below that the lower elevations are dominant in the southern part of the valley, making it more susceptible to flood events. The elevation ranges from −4 m to 0m denotes an area with an extremely high probability of flooding, whereas the elevation range from 66 m to 140 m indicates an area with a significantly lower risk of flooding (**Figure 3(a)**).

Flooding in an area depends on the length and slope angle of the area. For example, areas with low lengths and slope angles will experience flooding compared to areas with high lengths and slope angles [27]. The slope of the Lower Valley of Ouémé varies from a minimum of 0˚ to a maximum of 23.4˚. The slope map of the study area, depicted in **Figure 3(b)**, illustrates the categorization of slopes into five classes, ranging from gentle (0˚ - 0.643˚) to extremely steep (7.08˚ - 23.4˚).

Rainfall is a very important factor to consider in determining the risk of flooding because heavy rainfall causes high water, overflows the riverbeds and leads to flooding. **Figure 3(c)** shows a spatialization of heavy annual daily rainfall in the Lower Valley of Ouémé. The lowest rainfall amounts are found only in the northeast of Bonou. The heaviest rainfall is found mainly in Adjohoun and in the southwest of So-Ava.

The illustration provided in **Figure 3(d)** depicts the soil map of the area, which shows three types of soil in the Lower Valley of Ouémé. The Gleysols covering 73.4% of the study area are sandy, clayey and silty. This soil is classified as high risk for flooding due to its low infiltration rate. Then we have Nitosols which cover 15.2% and are soils that have a medium permeability. The last type of soil found in the area is Regosols which cover 11.4%. These are permeable soils and therefore allow the infiltration of water which reduces the risk of flooding.

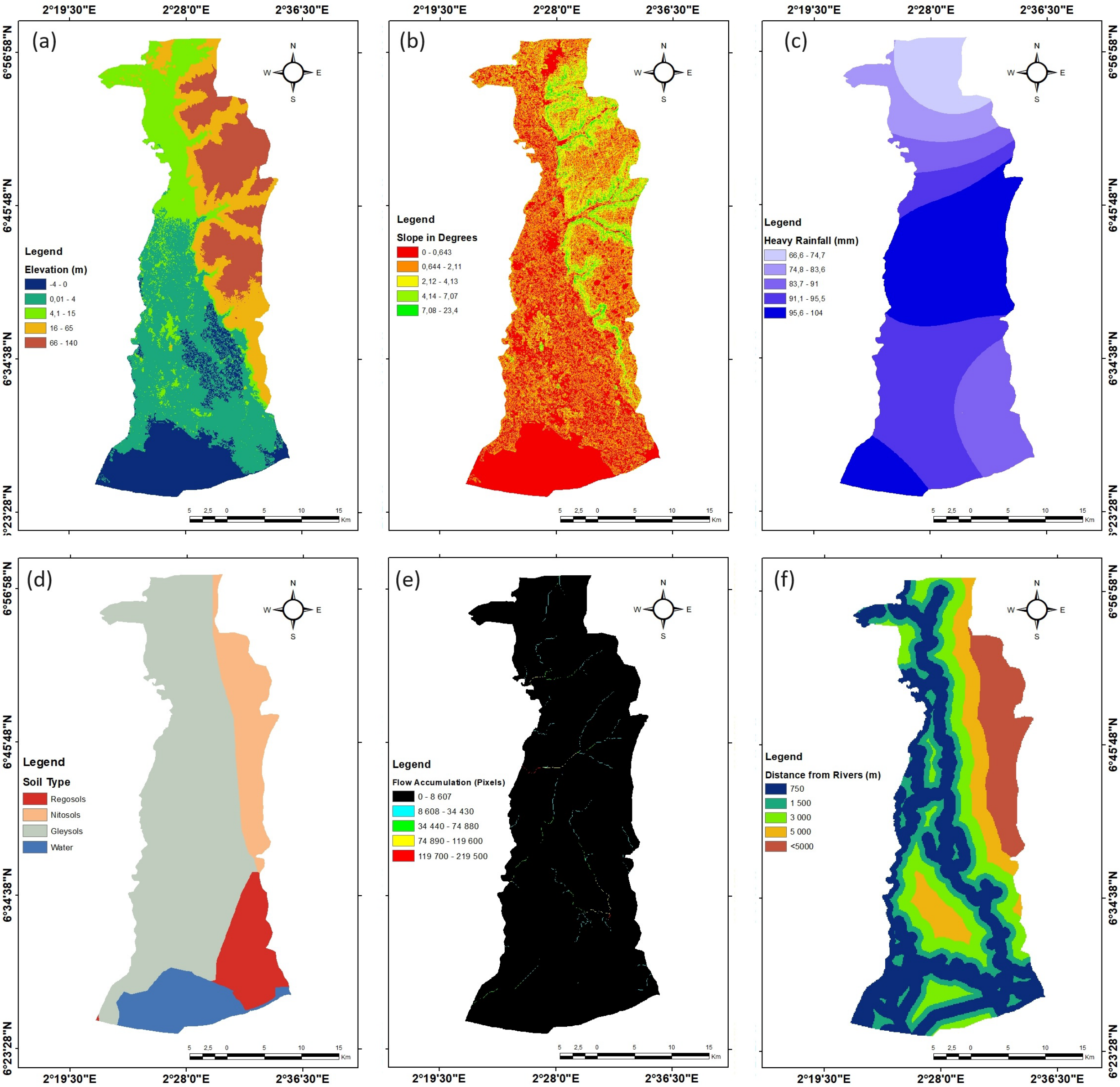

Figure 3. Flood hazard indicators. (a) Elevation; (b) Slope; (c) Rainfall; (d) Soil type; (e) Flow accumulation; (f) Distance from rivers.

Flow accumulation is regarded as a factor impacting the risk of floods in the Lower Valley of Ouémé. When there is a high flow accumulation, it indicates a correspondingly high risk of flooding [12]. The flow accumulation map is derived through a spatial analysis of the digital elevation model. In **Figure 3(e)**, the red and yellow indicate areas with important flow accumulation, whereas the green, light green, and background (black pixels) correspond to regions with moderate and low flow accumulation.

The river's proximity serves as a crucial factor in assessing the likelihood of floods since regions near the river encounter more frequent flooding compared to those located farther away from it, and vice versa. **Figure 3(g)** illustrates the distances from rivers within the designated study area. Given the fieldwork findings, regions situated within 750 m of the rivers are categorized as having an exceedingly elevated likelihood of flooding. Conversely, areas positioned at distances of 1500 m, 3000 m, 5000 m, and beyond 5000 m from the rivers are classified as having high, medium, low, and extremely low probabilities of flooding, correspondingly. According to Figure 3(f), the western and southern parts of the valley have more rivers that are close to each other, which increases its susceptibility to flash flooding.

3.2. Flood Exposure Indicators

Population density and land use were chosen as two distinct indicators to assess flood exposure (Table 2).

Table 2. Flood exposure indicators.

Flood Exposure Indicators	Land Use	Population Density
Land Use	1	3
Population Density	0.33	1
Total	1.33	4

Table 3. Land use type.

Land use classes	Trees	Grassland	Crops	Flooded vegetation	Scrub	Bare soil	Built areas	Water bodies
Percentage	38.90%	0.037 %	8.71%	3.63%	28.61%	0.0088 %	5.99%	14.11%

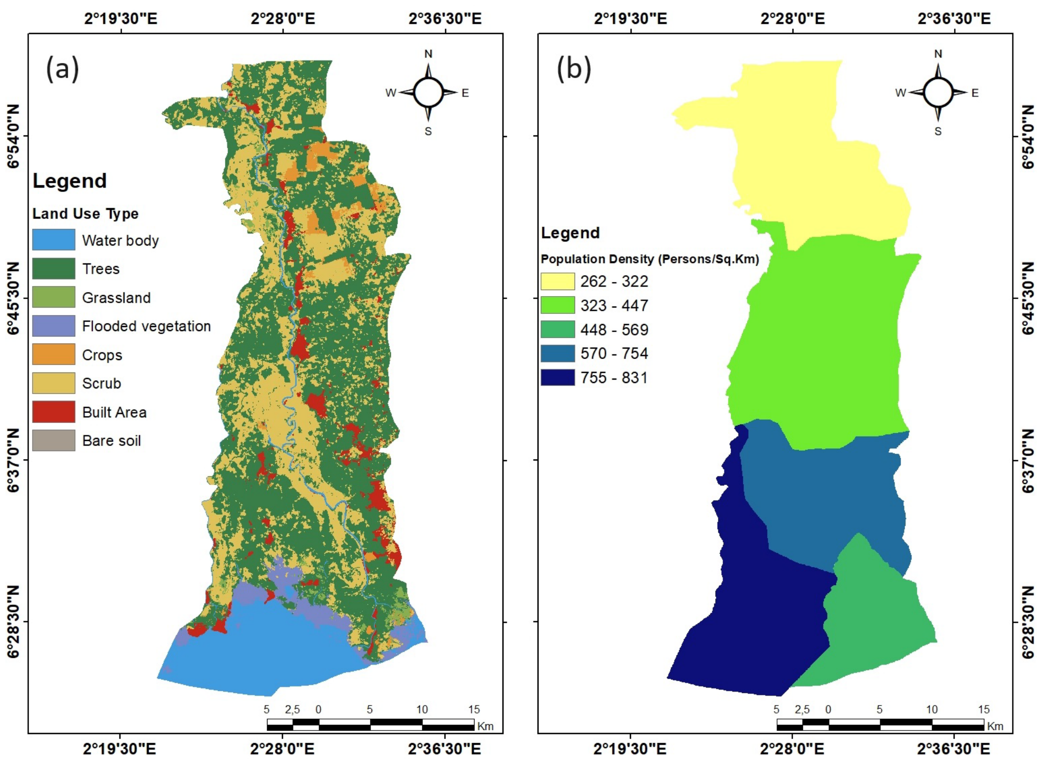

Figure 4. Flood exposure indicators. (a) Land use type; (b) Population density.

Figure 4(a) displays the land use map, categorized into eight distinct classes, specifically: trees, grassland, crops, flooded vegetation, scrub, bare soil, built areas and water bodies. The areas covered by these types of classes are shown in Table 3.

The map displaying the distribution of population density is regarded as a factor affecting the susceptibility to floods [36]. Anticipate increased sensitivity among communities undergoing challenging living conditions, such as malnourishment, overcrowding, and insufficient access to healthcare services. A map of population density, categorized into five classes, is displayed in Figure 4(b), with the highest density observed in So-Ava, populated by 755 - 831 individuals per square kilometer or per sq. km, and the lowest density in Bonou, with 262 - 322 individuals per square kilometer or per sq. km.

3.3. Flood Vulnerability Indicators

Table 4 shows the four flood vulnerability indicators that were chosen, which include the number of female population per square kilometer (female density), percentage of literacy, poverty index, and density of road network.

Density of Female Inhabitants

The susceptibility of regions to natural calamities, such as floods, is influenced by the concentration of women in those areas [27]. Females have the highest perception of risk among all vulnerable population groups due to their low income, low decision-making power, lack of mobility, cultural restrictions, and increased care and family responsibilities, women have more difficulty recovering from floods. Figure 5(a) showcases the map illustrating the density of women in the region. The commune of Bonou has the lowest density of women (145 - 157 Females/Sq/Km). So-Ava has the highest density of women.

The speed of recovery after flood impacts is determined by the presence of roads, including intercountry, intercity, and local roads. Figure 5(b) illustrates the concentration of road network in the study area. Dangbo and Adjohoun exhibit significant road density, both high and very high. The presence of a variety of roads, spanning from intercity to local, in the communes of Dangbo and Adjohoun contributes to their reduced vulnerability to floods.

A population with a high level of education can readily comprehend the gravity and characteristics of a calamity and possess the capacity to promptly react [27]. The level of literacy within the surveyed region significantly differs among different communities (Figure 5(c)). The low literacy rates (0% - 48.6%) are in the communes to the south of the Lower Valley, namely So-Ava and Aguégués. The high literacy rate (54.4% - 60%) is concentrated in Adjohoun and Dangbo. The considerable literacy rate in this area enables residents to comprehend the gravity and characteristics of natural calamities, as well as their ability to swiftly adjust and recuperate from these perils.

Table 4. Matrix comparing indicators of flood vulnerability.

Flood Vulnerability Indicators	Female Density	Road Network Density	Poverty index	Literacy Rate
Female Density	1.00	2.00	4.00	3.00
Road Network Density	0.50	1.00	2.00	2.00
Poverty Index	0.25	0.50	1.00	1.00
Literacy Percentage	0.33	0.50	1.00	1.00
Total	2.08	4	8	7

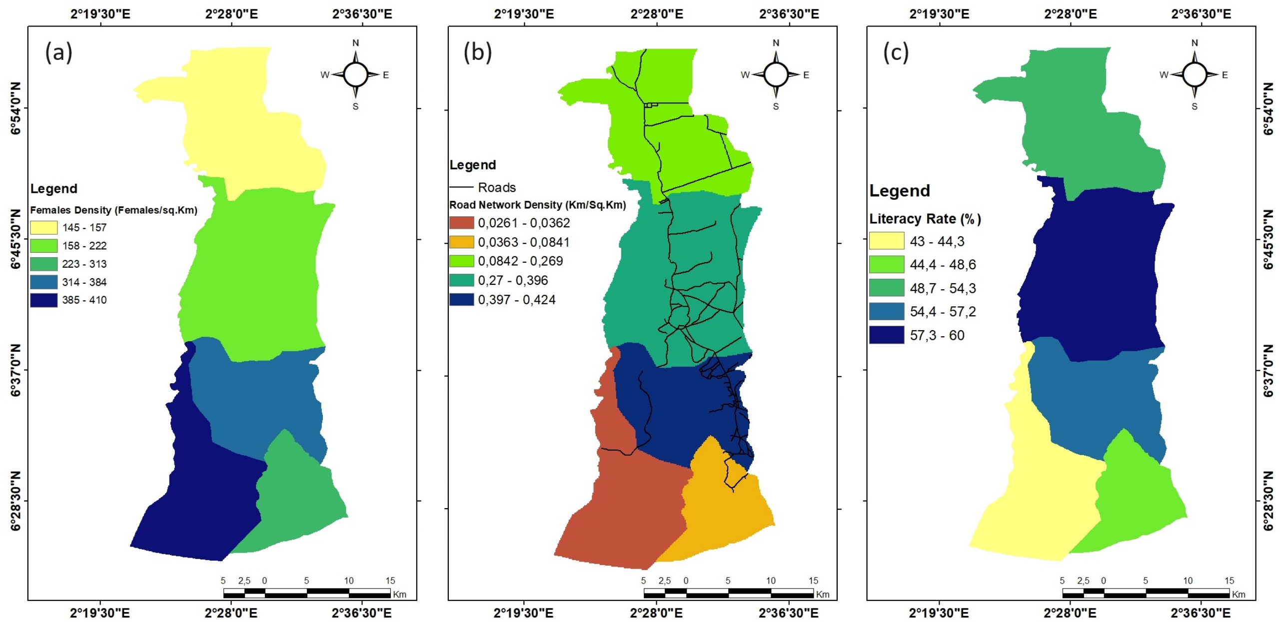

Figure 5. Flood Vulnerability Indicators. (a) Female population density; (b) Road network density; (c) Literacy Rate.

3.4. Standardized Indicators for Flood Risk Components

To facilitate comparison, qualitative data was assigned numerical values for each indicator, thereby rendering them dimensionless. The allocated values for the indicators can be found in Table 5, Table 6 below.

3.5. Weight Allocation

The tables labeled 1, 2, and 4 contain matrices that display the pairwise information for flood hazard, exposure, and vulnerability factors. It was determined that the CR values for flood hazard, exposure, and vulnerability are 1.8%, 0%, and 0.4% respectively. These values, being below 10%, indicate an acceptable degree of consistency [37]. Tables 4-6 provide an overview of the weight and ranking assigned to each element concerning hazard, exposure, and vulnerability. The flood hazard indicators have been assessed, and the resulting weights are as follows: distance from rivers, 29%; elevation, 26%; slope, 16%; soil type, 11%; drainage density, 8%; rainfall, 7%; and flow accumulation, 3%. This suggests that the primary factors affecting flooding events in the research region are the proximity to the river and the altitude. Nevertheless, the weights obtained from the vulnerability indicators are as follows: female population density, 48%; density of road network, 25%; rate of literacy, 14%; and poverty index, 13%. This suggests that the density of women in the population holds the most significant socioeconomic influence on the vulnerability to flooding within the examined region. The derived weights for the exposure indicators are land use (75%) and population density (25%).

Table 5. Categories of flood hazard indicators, along with their respective weighting and ranking.

Indicators	Percentage	Reclassified Indicator	Ranking	Hazard Indicators
Elevation (m)	26%	66 - 136	1	Very low
		16 - 65	2	Low
		4 - 15	3	Moderate
		0 - 3	4	High
		−4 - 0	5	Very High
Slope (˚)	16%	7.69 - 24.2	1	Very low
		4.66 - 7.68	2	Low
		2.57 - 4.65	3	Moderate
		0.949 - 2.56	4	High
		0 - 0.948	5	Very High
Rainfall (m)	7%	66.6 - 74.7	1	Very low
		74.8 - 83.6	2	Low
		83.7 - 91	3	Moderate
		91.1 - 95.5	4	High
		95.6 - 104	5	Very High
Drainage density (Km/Km^2)	8%	0 - 0.36	1	Very low
		0.361 - 1.08	2	Low
		1.09 - 1.92	3	Moderate
		1.93 - 2.97	4	High
		2.98 - 6.11	5	Very High
Flow accumulation (px)	3%	0 - 1637	1	Very low
		1638 - 12,280	2	Low
		12,290 - 45,830	3	Moderate
		45,840 - 121,100	4	High
		121,200 - 208,700	5	Very High
Distance from Rivers (m)	29%	3611 - 6622	1	Very low
		2079 - 3610	2	Low
		1170 - 2078	3	Moderate
		545.4 - 1169	4	High
		0 - 545.3	5	Very High
Soil type	11%	Regosols (Loamy sand)	2	Low
		Nitosols (Sandy loam)	3	Moderate
		Gleysols (Loam)	4	High

Table 6. Categories of flood vulnerability indicators, along with their respective weighting and ranking.

Indicators	Percentage	Reclassified Indicator	Ranking	Vulnerability
Female population density (females/square kilometer)	48%	145 - 157	1	Very low
		158 - 222	2	Low
		223 - 313	3	Moderate
		314 - 384	4	High
		385 - 410	5	Very High
Road network density (Km/Km^2)	25%	0.396 - 0.424	1	Very low
		0.269 - 0.396	2	Low
		0.0841 - 0.269	3	Moderate
		0.0362 - 0.0841	4	High
		0.0260 - 0.0362	5	Very High
Poverty index (%)	13%	16 - 20.2	1	Very low
		20.3 - 32.2	2	Low
		32.3 - 39.1	3	Moderate
		39.2 - 50.2	4	High
		50.3 - 61	5	Very High
Literacy rate (%)	14%	57.3 - 60	1	Very low
		54.4 - 57.2	2	Low
		48.7 - 54.3	3	Moderate
		44.4 - 48.6	4	High
		43 - 44.3	5	Very High

3.6. Mapping Flood Hazards

Figure 6(a) displays the flood hazard map for the Lower Valley of Ouémé, depicting the various areas susceptible to flooding. It exhibits five categories of hazard levels, spanning from extremely low to extremely high. The extremely high and high hazard classifications encompass 5.05% and 47.85% of the analyzed area, primarily found within the So-Ava, Dangbo, and Aguégués communities. These regions are primarily recognized for their predominantly moderate gradients and low altitudes. Other factors responsible for the high-risk intensity in these areas are the overflowing of the river due to water coming mainly from the north, the strong increase in water depth during the rainy season, the encroachment of aquatic grasses along the various watercourses, and the extraction of sand by the local populations. The elevated level of hazards in this region has caused it to be vulnerable to flooding.

In addition, around 24.83% of the study area is classified as the moderate class, which includes part of the commune of Bonou, Adjohoun and Dangbo. Moderate hazard areas are also found in the other communes of the valley, but in very small proportions. In contrast to the southwestern part of the valley, the northeastern part is subject to low hazard classes that are spatially distributed throughout the area and cover approximately 22.27% of the valley. These areas

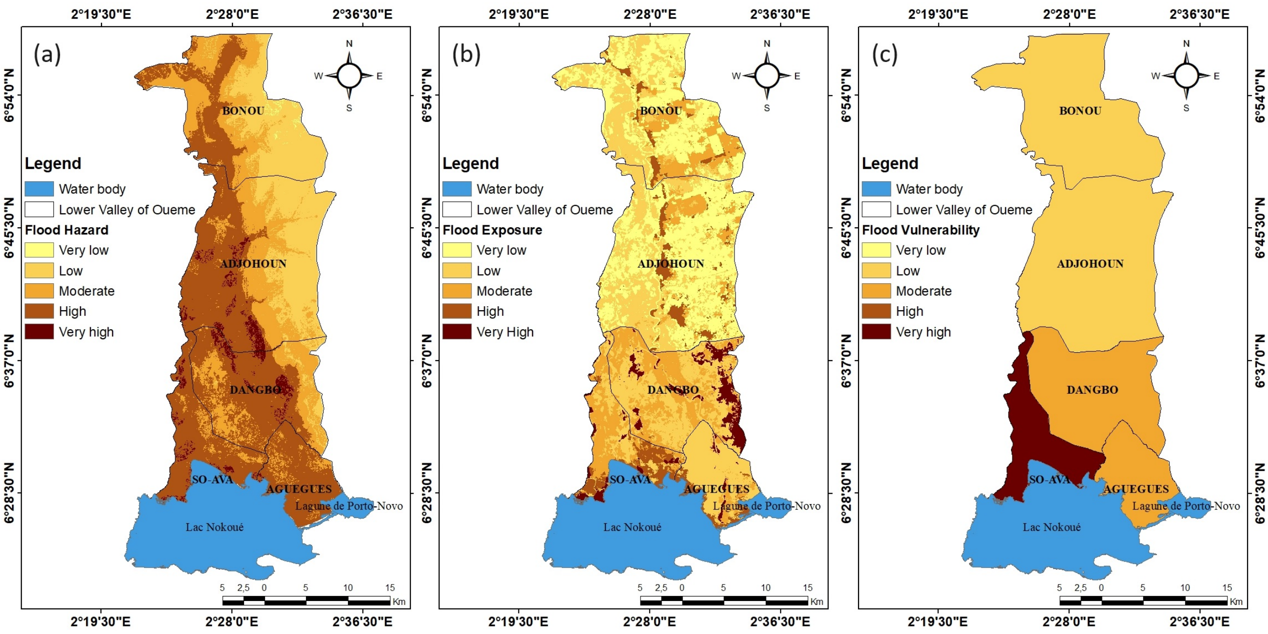

Figure 6. (a) Flood hazard layer; (b) Flood exposure layer; (c) Flood vulnerability layer.

include the communes of Bonou and Adjohoun. High elevations, sharp gradients, stony and gritty soils, moderate precipitation, and a comparatively sparse network of waterways distinguish these regions.

3.7. Map of Flood Exposure

Figure 6(b) illustrates the flood exposure map of the surveyed region, depicting five distinct exposure categories spanning from minimal to extreme. Approximately 3.32% and 7.07% of the study area are allocated to the very high and high exposure classes respectively. These regions are predominantly characterized by urban development and barren land use, accompanied by important population concentrations. These locations are distributed in small proportions throughout the municipalities. The medium exposure class covers 17.61% of the valley and the categories of low and extremely low exposure account for 44.95% and 27.04% of the Valley respectively. These categories encompass regions characterized by agricultural activities, lush vegetation, and sparse human habitation. Specifically, the majority of the Bonou and Adjohoun communes, along with uninhabited areas in other communes, fall under the classifications of low and extremely low vulnerability.

3.8. Map of Flood Vulnerability

Figure 6(c) depicts the flood vulnerability map for the examined region, showcasing five distinct vulnerability categories spanning from extremely low to extremely high. Approximately 19.15% of the studied region comprises the category of extremely susceptible. These areas predominantly exhibit a dense female population, low literacy levels, substantial poverty, and inadequate road networks. Thus, the commune of So-Ava represents the highest flood vulnerability class. The medium vulnerability class covers 27.72% of the valley, *i.e.*, the communes of Dangbo and Aguégués. The low vulnerability classes cover 53% of the Valley which corresponds to high literacy rate, significant economic activities, and high residency. This is consistent with some previous findings in the study area [27]. Places such as Bonou and Adjohoun constitute the low vulnerability classes.

This study analyzed "vulnerability" and "exposure" as central concepts in understanding disasters, their magnitude and their impact [38] [39]. This, therefore, has significant implications for the design of sustainable flood management strategies. Integrating these concepts into flood risk assessment has provided data on the location of areas with specific assets such as communities, the environment or properties that are prone to serious incidents resulting in loss of life, damage, contamination or devastation. Adverse events confined to areas of minimal susceptibility or exposure do not turn into disasters [40]. Nevertheless, disasters emerge when faced with inadequate infrastructure, limited disaster preparedness plans, high population density, and underdeveloped areas.

3.9. Map of Flood Risk

Figure 7(a), depicting the flood map, indicated the classified flood risk into five levels, varying from extremely low to extremely high. The figure illustrates that the study area consists of proportions of 20%, 48.4%, and 30%, for the respective risk categories of high, moderate, and low. The areas classified as high and extremely high-risk are distinguished by their close proximity to rivers, small slopes and altitudes, abundant network of channels, limited soil permeability, dense population, concentration of vulnerable individuals, low literacy rate, moderately elevated rainfall, and urban development. Approximately 21.5% of the valley encompasses regions with elevated or extremely elevated vulnerability to flooding. Primarily located in So-Ava, with some portions in Aguégués and Dangbo, the study area identifies communities at significant risk of flooding. Very small portions of high-risk areas are found in Adjohoun and Bonou along the banks of the Ouémé River. Approximately 48.4% of the analyzed area falls into the moderate risk category, while 30.1% consists of low and extremely low flood risk zones. These risk categories demonstrate significant prevalence in the territories of Bonou and Adjohoun, which are regions known for their steep gradients and elevated elevations, permeable soil, lush vegetation, and use of forested areas. These areas also exhibit exceptionally low population density and remarkably high rates of literacy and income.

The assessment holds great significance for the government, non-governmental organizations (NGOs), and other planners, as it aids in prioritizing resource distribution to combat floods. Additionally, it determines the geographical scope of the flood perimeter, which aids in conducting evacuation drills, assisting insurance companies, and supporting relief agencies [41].

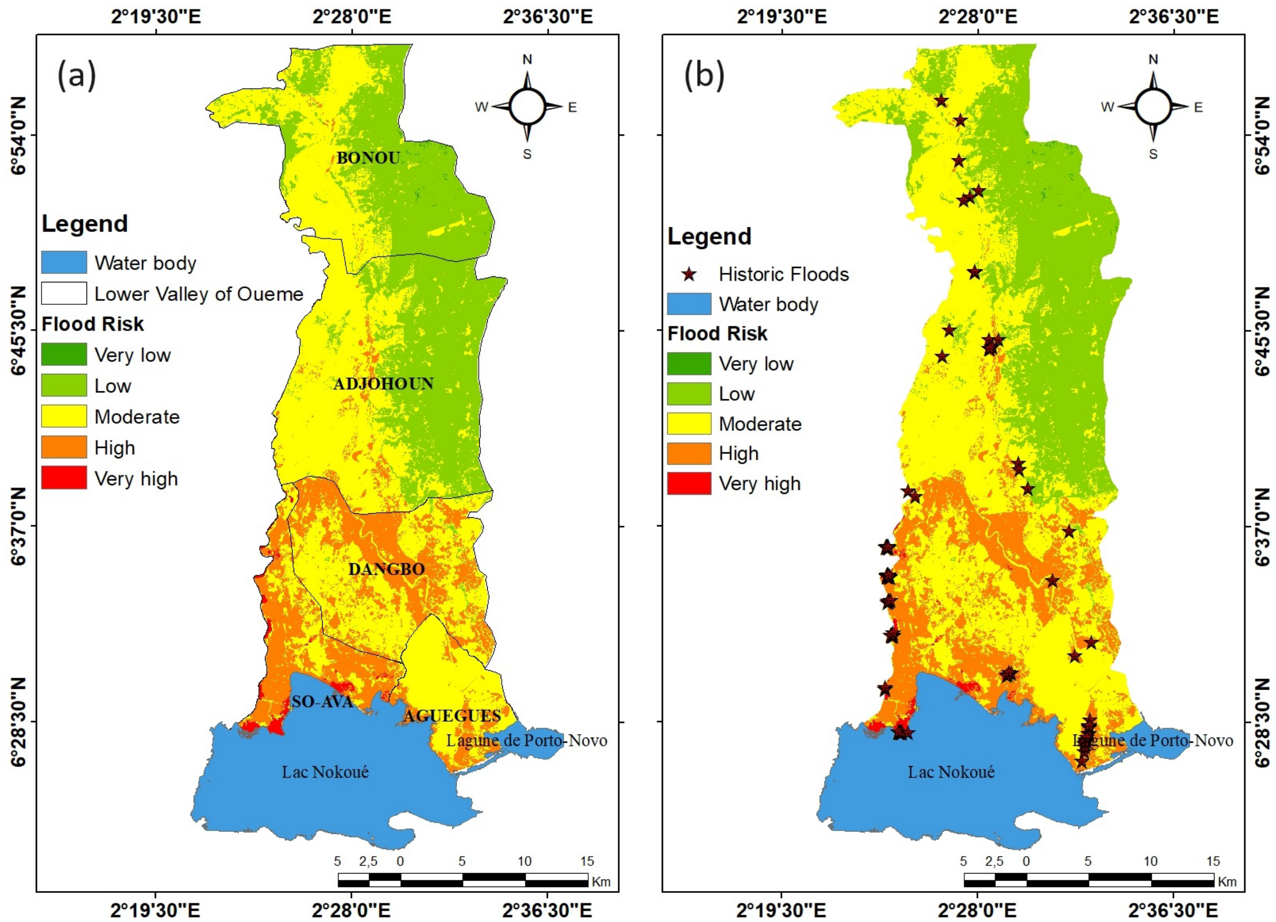

Figure 7. (a) Flood risk map post AHP examination; (b) Approved flood risk chart of the Lower Valley of Ouémé.

3.10. Evaluation of Flood Risk Map

The flood risk map for the Lower Valley of Ouémé is displayed in Figure 7(b), demonstrating that it aligns well with the survey data gathered in the study region. The figure illustrates that areas with historical flood occurrences correspond to high and very high flood risks, whereas the communes of Bonou and Adjohoun, characterized by elevated altitudes and slopes, exhibit low and very low flood risks. Out of the 160 surveyed areas known to have encountered one or multiple floods, 141 were situated in high and very high flood-risk regions. Moreover, only 17 historical flood events were recorded in moderately flood-prone areas, while low flood-risk areas experienced only 2 flood events. Consequently, this confirms the precise predictability of flood-prone areas through the implemented methodology.

The objective of sustainable flood management approaches is not to eradicate flood risk, but to reduce and handle it [42]. Overall, flood risk control can be broken down into three elements: a) readiness and preparation for the possibility of a risk escalating into a catastrophe, at both the personal and community levels; b) the creation of strategies (such as planning and preparation) to cope with the reaction to the unparalleled threat; and c) the prompt response measures needed to recover from the crisis [42] [43].

The primary objectives of structural measures to reduce floods are to store, redirect, and confine floodwaters [43]. These measures involve various techniques to restore streams, prevent floods, and maintain riverbeds. Due to the significant impact of floodwater in the region, protecting the large population nearby requires the protection, maintenance, monitoring, and modification of these structures. Activities like sand mining and dike construction have caused alterations in the stream and channel morphology, resulting in the submergence of farmland, villages, and roads. Therefore, frequent monitoring and assessment in vulnerable areas are necessary. Non-structural strategies involve relocating infrastructure away from bodies of water and employing architectural techniques for flood mitigation [44]. Land-use planning and zoning practices can also reduce flood risks, and flood insurance can provide compensation for losses [27] [45]. Educating and training community members in flood risk reduction is crucial, particularly for highly vulnerable communities with limited literacy levels.

4. Conclusions

This study examines the primary elements and catalysts of flood hazard, exposure, and vulnerability through a quantitative and qualitative analysis employing a multi-criteria statistical technique. The suggested approach revealed that roughly 25% of the southern region in So-Ava, Aguégués, and Dangbo localities is comprised of extensive and significant flood-prone areas. The Northeast region of the valley primarily experiences low and extremely low levels of risk. The flood risk maps for various timeframes yield similar results, consistent with the existing assessment of flood risk. This similarity arises because the rainfall in the Lower Valley of Ouémé contributes only a minor proportion (7%) to the frequency of floods in this particular area. The research also uncovers that flood risk is affected differently by indicators of flood hazard, exposure, and vulnerability. For instance, a significant flood hazard does not always result in elevated flood risk. Furthermore, the results are validated and agree with the collected data on the flood risk distribution. Therefore, the study's findings might prove beneficial in identifying elements that enhance resilience and could be integrated into forthcoming planning choices regarding the management of flood risks. However, a limitation of the applied methodology, namely the AHP, is the subjectivity linked to the weights considered, even though this choice was based on the literature. Other methods of flood risk assessment could be tested such as hydraulic modelling combined with socioeconomic analysis.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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