Journal of Geoscience and Environment Protection, 2026, 14(1), 265-297
https://www.scirp.org/journal/gep
ISSN Online: 2327-4344
ISSN Print: 2327-4336

Community-Level Flood Risk Assessment and Mapping in the Lower Ouémé River Basin, Benin

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How to cite this paper: Assogba-Ballè, R. G., Linsoussi, C. A., Ahouansou, D. M. M., & Sintondji, L. O. C. (2026). Community-Level Flood Risk Assessment and Mapping in the Lower Ouémé River Basin, Benin. *Journal of Geoscience and Environment Protection, 14,* 265-297.
https://doi.org/10.4236/gep.2026.141015

Received: November 22, 2025
Accepted: January 23, 2026
Published: January 26, 2026

Abstract

Understanding and mapping community vulnerability to hydroclimatic risks are critical prerequisites for effective flood disaster management and resilience planning. This study applies the IPCC AR5 framework to assess and map flood risk across 89 villages in the Lower Ouémé Valley, Benin, with the goal of spatializing risk levels to better inform local adaptation and decision-making. An integrated approach combining participatory diagnosis and spatial modeling was adopted. Data were collected at the community level using KoboCollect, and a set of indicators representing the three components of risk hazard, exposure, and vulnerability were developed, normalized, and weighted according to the AR5 framework. Thematic maps were then generated in QGIS to visualize spatial variations in risk. The results indicate that approximately 72% of the villages face medium to very high levels of flood risk, reflecting significant disparities associated with flood duration, water depth, population density, and poverty index. The most affected zones require priority attention for the implementation of early warning systems and adaptive response strategies. These findings emphasize the need for territorialized climate risk governance grounded in participatory and scientifically validated mapping approaches. The study proposes a replicable methodology for spatial flood risk assessment that operationalizes the IPCC AR5 conceptual framework at the local scale. Future work could enhance this approach through dynamic risk modeling and the integration of high-resolution satellite data to improve the spatial and temporal accuracy of flood risk prediction.

Keywords

Flood Mapping, AR5, Flood Risk, Vulnerability, Oueme Valley

1. Introduction

Floods rank among the most devastating natural hazards, particularly in developing nations, where their impacts are both social and economic. They lead to loss of life, forced displacement of populations, and the destruction of infrastructure, homes, and agricultural land (Koubodana Houteta et al., 2025). Climate change driven by global warming has altered the occurrence and magnitude of extreme hydrological events in many parts of the globe. As a consequence of climate change, both the intensity and frequency of rainfall events have increased (Ranasinghe et al., 2021). When coupled with the rising river discharges observed across West Africa, this trend has led to more frequent occurrences of river flooding. In recent years, floods have become more common in the region. Benin has faced devastating flood incidents that caused deaths, destroyed properties, and left thousands of people homeless (Hounkpè et al., 2022; Koubodana Houteta et al., 2025).

In the Lower Valley of Oueme River Basin, flooding is a recurrent phenomenon, as the area is regularly exposed to such events. Each year, floods occur with varying magnitudes and impacts. The most notable episode remains the 2010 flood, which caused a sudden and widespread rise in the water levels of major rivers and their tributaries throughout the country. This disaster severely affected approximately 680,000 people across 55 villages, leading to the displacement of about 150,000 individuals. It also destroyed more than 55,000 houses, 450 schools, and 90 health centers, while triggering outbreaks of waterborne diseases such as cholera, malaria, and diarrheal infections. The economic toll was substantial, with estimated losses of around 160 million USD, nearly 200,000 hectares of cropland devastated, and approximately 80,000 livestock lost (Ferdinand et al., 2025).

In addition to these large-scale events, the Lower Valley of Oueme River Basin like the whole region also experiences seasonal floods caused by intense and extreme rainfall. Although these are generally less severe, they occur on a recurrent basis. Moreover, if current trends in climate change persist, combined with the growing population settling in flood-prone areas, ongoing deforestation, the disappearance of wetlands, and the rising mean sea level, catastrophic floods are expected to become more frequent in the coming decades (Ferdinand et al., 2025).

Considering the substantial social, economic, and environmental impacts of flooding, accurately identifying villages exposed to high flood risk is essential for the design and implementation of well-targeted interventions during flood crises. In recent years, flood risk assessments within the Oueme catchment have increasingly utilized Geographic Information Systems (GIS) and multi-criteria analysis to improve the spatial delineation and prioritization of flood-prone areas (Bossa et al., 2024; Ferdinand et al., 2025; Quenum et al., 2022). These integrative approaches combine hydrological parameters, socio-economic vulnerability indicators, and exposure factors to generate comprehensive flood risk maps. Findings from recent studies within the Oueme floodplain reveal that approximately 21.5% of the lower valley is classified as being at high or very high flood risk, with the southern parts of the basin most severely affected (Bossa et al., 2024; Ferdinand et al., 2025). However, despite these advances, a significant research gap persists: most existing studies have concentrated on flood risk mapping at the municipal scale, often neglecting detailed assessments of flood vulnerability and composite flood risk at the village level across the entire Oueme River Basin.

A combination of factors including inadequate infrastructure, limited resources for disaster preparedness and response, and high population density in flood-prone areas, often amplifies the destructive potential of floods across various localities leading to severe human, economic, and environmental losses (Raza & Hatab, 2025). Previous studies suggest that effective adaptation to flood hazards requires the identification of vulnerable communities, an understanding of the factors contributing to their susceptibility, and an assessment of their resilience capacities to mitigate adverse outcomes. Furthermore, the analysis of vulnerability and resilience has been instrumental in advancing hazard research and has played a pivotal role in shaping more effective disaster management and risk reduction strategies (GIZ & EURAC, 2015; Raza & Hatab, 2025).

In response, successive Beninese governments, together with their development partners (Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ)), have in recent decades progressively integrated the concepts of vulnerability, risk, and resilience (GIZ & EURAC, 2015, 2017) into policy frameworks and intervention programs aimed at strengthening preparedness and enhancing the adaptive capacity of rural communities facing escalating flood risks (Hounkpè et al., 2022). In this context, assessing the vulnerability and resilience of Beninese households to flooding is essential for designing context-specific disaster management strategies and improving preparedness within flood-prone rural areas.

As studies on flood vulnerability and risk assessment have evolved, hazard researchers have increasingly advocated for the integration of social vulnerability parameters into comprehensive frameworks for flood risk assessment and management. Most of these studies have relied on traditional index-based approaches, in which vulnerability factors are assigned weights and subsequently aggregated according to criteria derived from existing literature or expert judgment. In some cases, researchers have employed more advanced data aggregation techniques to compute composite risk indices, integrating feedback from stakeholders to refi ne the weighting of variables. Despite these methodological advances, there remains a notable gap in the literature regarding the use of IPPC AR5 methodology in vulnerability and risk assessment.

To date, no detailed study has been conducted to assess integrated flood risk at the village scale within the Ouémé River Basin. In light of this gap, the present study aims to evaluate the integrated flood risk in the Lower Ouémé River Valley by applying the IPCC AR5 risk framework. The main objective is to develop a robust and credible approach for assessing flood vulnerability and risk at the village level, thereby enabling more precise and context-specific intervention strategies.

2. Materials and Methods

2.1. Study Area

The present study was carried out in the lower Ouémé valley in Benin, West Africa as shown in **Figure 1**. The Ouémé River basin is located between latitudes of 10˚09.55'N - 6˚20.23'N and longitudes 1˚30'E - 2˚30'E and is relatively flat (Bodjrènou et al., 2025; Hounkpè et al., 2022). It spans from the source of the Ouémé River in the Tanéka mountains in northern Benin to the Atlantic Ocean (South Benin). With a drainage area of almost 50,000 km^2, it covers 41.14% of Benin's total area (Bodjrènou et al., 2025). In the southern part of the basin, the Oueme River expands into a vast floodplain covering approximately 1200 km^2, forming what is known as theOueme Delta (Osseni et al., 2022). This delta is made up of two main rivers: the Oueme and the Sô which both serve as major tributaries to Lake Nokoué, the largest water body in Benin, with an area of about 150 km^2 during low-water periods (Le Barbé et al., 1993). The delta system is hydrologically connected to the Atlantic Ocean through the Cotonou and Porto-Novo lagoons.

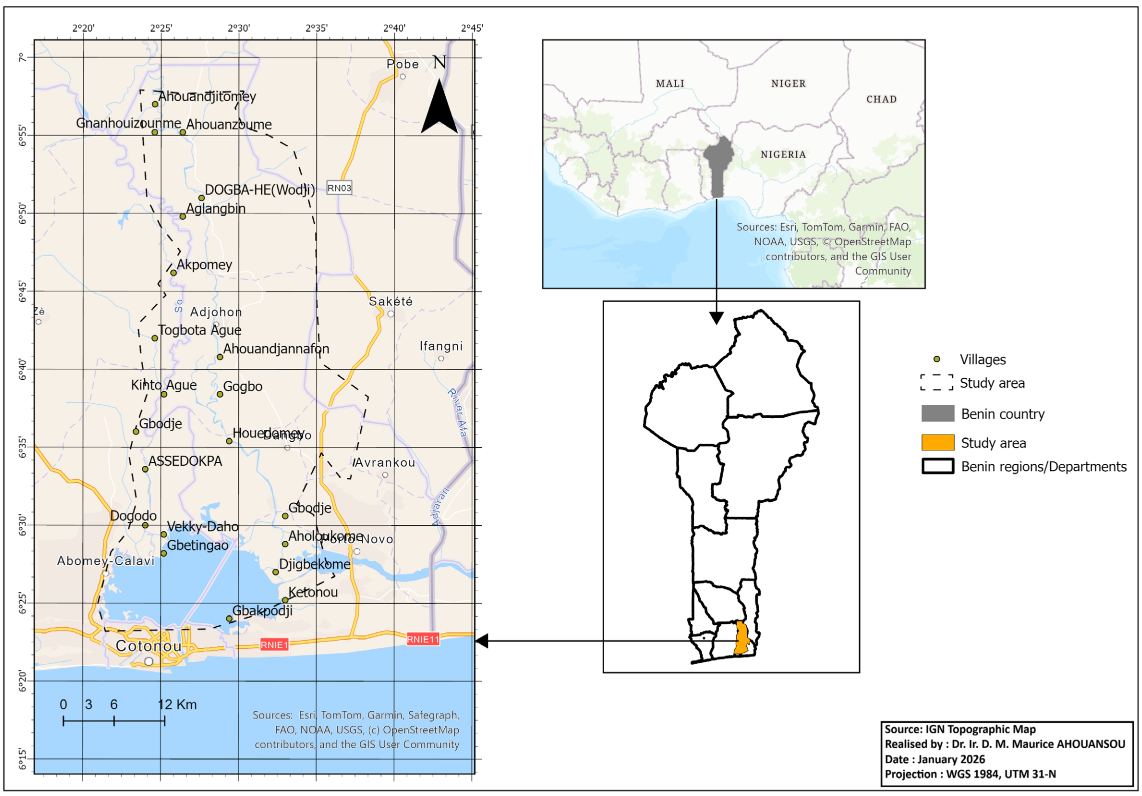


Figure 1. Geographical position of Lower Valley of Oueme River Basin.

The Oueme Delta is characterized by a relatively flat topography, with an elevation difference of approximately 20 meters from south to north, which facilitates the lateral spreading of watercourses, as well as processes of erosion and siltation (Ferdinand et al., 2025). The Ouémé River itself exhibits a very gentle slope—only about 5 meters of elevation change over 85 kilo meters within the floodplain from north to south (Le Barbé et al., 1993) and in certain sections, the gradient decreases to just a few centimeters per kilometer. This low-lying terrain is highly favorable for agricultural activities; however, it also poses significant challenges for drainage during the rainy season, thereby increasing the vulnerability of local communities to flooding.

The seasonal migration of the Intertropical Convergence Zone (ITCZ) governs the rainfall pattern across Benin. In the southern part of the country, this dynamic results in two distinct rainy seasons: a major one from April to July, linked to the northward movement of the ITCZ, and a shorter one from September to November, associated with its southward retreat. Conversely, northern Benin, where the ITCZ remains quasi-stationary around August, experiences a single, continuous rainy season (Ferdinand et al., 2025). These rainfall regimes are vital for recharging the aquifers that sustain the Ouémé River at its source (Ferdinand et al., 2025; Lawin et al., 2019). Mean annual precipitation is estimated at about 1300 mm in the headwaters and increases to approximately 1500 mm across the floodplain (Le Barbé et al., 1993). The spatio-temporal variability of rainfall induces high river discharges between August and November, often triggering floods around Lake Nokoué and its surrounding watersheds. During this period, the Oueme River experiences substantial rises in water levels, with flow rates ranging from a few tens of cubic meters per second during low-flow periods to over 1000 m^3/s during peak floods (Ferdinand et al., 2025; Lawin et al., 2019; Okpeitcha et al., 2022).

The Ouémé Delta encompasses 18 communes, including three urban and fifteen rural ones. Its total population is estimated at approximately 3,560,089 inhabitants, comprising 1,730,164 men and 1,829,925 women (Sossa et al., 2024). The region hosts cosmopolitan communities, particularly in urban centers. The principal indigenous ethnic groups are the Aïzo and the Toffinnu—literally translated as "people of the water"—who are mainly settled around the Sô River and Lake Nokoué. In contrast, the Xémè are predominantly concentrated along the Oueme River and around the Porto-Novo Lagoon (Sossa et al., 2024).

Agriculture constitutes the primary livelihood activity in the Oueme Delta, engaging over 90% of the population and representing more than one-third of Benin's faring households (Sossa et al., 2024). Rainfall plays a decisive role in the success of agricultural production in the delta, where only about 4.36% of arable land is irrigated. Nevertheless, off-season cultivation remains significant in irrigated zones, particularly given the occurrence of annual floods lasting approximately two to four months. In addition to crop farming, about 11% of the delta's inhabitants engage in traditional fishing, while livestock rearing is generally practiced on a small domestic scale (Sossa et al., 2024). The spatial distribution of economic activities follows a clear pattern: populations living near rivers predominantly depend on fishing, whereas those in the plains focus mainly on agricultural production.

Each year, communities in the Oueme Delta are exposed to seasonal flooding that typically occurs between August and October. While this annual flow provides significant benefits derived from the wetlands such as fertile soils, fishing opportunities, and water availability; the recurrent nature of floods increasingly limits the sustainable enjoyment of these advantages. This study, therefore, aims to assess integrated flood risk at the village scale within the Oueme Delta, with particular attention to the implications of these recurring flood events.

2.2. Methods

2.2.1. Data Collection

In this study, Community-level data were collected through field surveys using the KoboCollect mobile platform, enabling the systematic capture of socio-economic, demographic, and environmental information from local households.

First, a list of 89 regularly flooded villages within the Ouémé Delta was obtained from the Benin Agency of Civil Protection. In each selected village, focus group discussions (FGDs) were organized to gather qualitative insights on community experiences with flooding and local coping mechanisms. To ensure the representativeness of different socio-professional groups within the community, participants were purposefully selected to include two representatives each from key stakeholder categories namely farmers, fishers, livestock breeders, women engaged in agricultural processing, elders, merchants, artisans, youth, local non-governmental organizations (NGOs), and local authorities. This participatory approach allowed for the collection of diverse perspectives on flood impacts, vulnerability factors, and community-based adaptation practices.

Secondly, following each focus group discussion, field visits were conducted within the respective villages to collect the geographical coordinates of flood impact zones and to document visible evidence of flood damage, such as debris deposits, erosion marks, and damaged infrastructure. These observations were georeferenced using handheld Global Positioning System (GPS Garmin 62s) devices to support the spatial analysis of flood extent and intensity across the Oueme Delta.

Finally, individual interviews were conducted using the snowball sampling technique (Parker et al., 2019) to capture personal experiences related to flood impacts and the indigenous adaptation strategies developed by community members. These interviews also served to triangulate and validate the information gathered during the focus group discussions. In addition, respondents were invited to share their perceptions of the effectiveness of the National Flood Early Warning System and to evaluate the forms of governmental assistance they had received during past flood events. This complementary qualitative approach enriched the understanding of local adaptive responses and institutional support mechanisms in the Oueme Delta.

The sample size was determined using Cochran's formula, which accounts for factors such as population size, margin of error, and confidence level. This equation, widely applied in social and environmental research, is used to estimate the required sample size (N) for a desired level of precision when dealing with proportions (Sathyanarayana et al., 2024). It is expressed as follows:

$$N = \frac{Z^2 \times P \times (1 - P)}{E^2} \tag{1}$$

where N is the sample size for an infinite population, Z represents the standard normal deviation corresponding to the desired confidence level (e.g., 1.96 for 95%), P is the estimated proportion of the population possessing the attribute of interest (0.5), and E denotes the acceptable margin of error (0.05).

By applying this formula, the theoretical sample size was estimated at 385 individuals to be interviewed. In social science research, a sample size within the range of 384 to 400 respondents is generally considered adequate for large populations when using a 95% confidence level and a 5% margin of error. This range ensures a statistically reliable representation of the target population while maintaining practical feasibility in field data collection (Sathyanarayana et al., 2024). The final sample size was determined by applying proportionality coefficients (k_i) to the theoretical sample size previously estimated at 384 individuals. These coefficients were obtained using the Equation (2).

$$k_i = \frac{v_i}{V} \tag{2}$$

where v_i is the number of villages in each commune and V represents the total number of villages (89) concerned by this study. This adjustment ensured that the number of respondents selected from each village reflected its relative population size within the total population of the 89 regularly flooded villages. The proportionality-based allocation is expressed as follows:

$$n_i = \frac{k_i \times N}{v_i} \tag{3}$$

where n_i is the number of respondents selected from each village; k_i represents the proportionality coefficient of each commune; N is the theoretical sample size estimated at 385 and v_i the number of villages in each commune.

After applying Equations (1, 2 and 3), the minimum number of respondents per village was estimated at 4.32, which was rounded up to 5 respondents per village. Accordingly, the final sample size consisted of 445 respondents across all 89 villages included in the study. **Table 1** presents the distribution of respondents by commune, along with the corresponding number of villages surveyed and participants interviewed in each.

In summary, the data used in this study were collected through 89 focus group discussions and 445 individual interviews conducted across the study area. The field survey took place between July and August 2024, encompassing both the qualitative and quantitative components of data collection.

Table 1. Number of villages and number of respondents per commune.

Communes	Number of villages	Number of respondents
Abomey-Calavi	1	5
Adjohoun	7	35
Aguégués	10	50
Bonou	6	30
Dangbo	8	40
Ouinhi	6	30
Sèmè-Kpodji	3	15
Sô-Ava	17	85
Toffo	5	25
Zagnanado	12	60
Zê	5	25
Zogbodomey	9	45
Total	**89**	**445**

2.2.2. Description of the Impact Chain

To analyze the level of flood risk faced by villages affected by the overflow of the Oueme River, the impact chain was first defined, followed by the identification of the factors considered in the risk assessment. Relevant factors were selected to represent each component of the impact chain. For instance, adaptation and survival strategies during flood crises and access to information were identified as key factors for assessing the adaptive capacity component. These factors were subsequently operationalized through measurable indicators. In the above example, the number of survival and adaptation strategies reported in each village was used as an indicator to evaluate the adaptive capacity of that village.

The concept of risk defined in IPCC AR5, refers to the set of potential consequences related to climate (i.e., climate impacts or effects) on elements of value such as resources, human populations, ecosystems, and cultural assets (GIZ & EURAC, 2017). In this study, a flood risk refers to the set of potential consequences associated with flooding on elements of value such as human lives, infrastructure, ecosystems, and economic or cultural assets. It represents the likelihood and magnitude of adverse impacts resulting from the interaction between flood hazards and the exposure and vulnerability of affected systems. Typically, any given area or community is subject to multiple types of flood risks, depending on the intensity, frequency, and spatial extent of flood events. Thus, flood risk is conceptualized as a function of three interrelated components hazard (Danger), exposure and vulnerability (Equation (4)) which together determine the potential magnitude and likelihood of adverse flood impacts.

$$\text{Risk} = f\left(\text{Hazard}\left(\text{Danger}\right), \text{Exposure}, \text{Vulnerability}\right) \quad (4)$$

According to the IPCC AR5 methodology [11], a Hazard (Danger) refers to a specific threat to a given socio-ecological system or its components (i.e., the exposed elements). A hazard may take the form of a climatic event, such as heavy rainfall, or a direct physical impact, such as flooding. Whenever possible, the probability of occurrence of a specific hazardous event or trend should be estimated. In this context, hazards can be defined as critical climatic events or physical impacts—for example, extreme rainfall, extreme temperatures, or severe flooding.

In this study, three main elements were considered as flood hazards. These include the maximum water levels observed in the villages during flood events caused by the overflow of the Oueme River, the average duration of flooding in each village, and the number of flood occurrences recorded over the past ten years (**Table 2**).

Table 2. Hazard index parameters.

Parameters	Description	Units
Flood depth	Maximum water levels during flood event	*m*
Flood duration	Average duration of flooding	*month*
Flood frequency	Flood occurrences recorded over the past ten years	-

In the IPCC AR5, the term "*Exposure*" refers to specific elements (or elements at risk) that are subject to potential harm such as people, infrastructure, or ecosystems (GIZ & EURAC, 2017). The degree of exposure can be expressed in absolute numbers, densities, or proportions of these elements at risk; for instance, the population density within an area affected by flooding. In this study, the exposure component included several elements such as the extent of flooded farmlands, the number of houses destroyed, and the roads, health centers, and schools rendered inaccessible during flood events (**Table 3**).

Table 3. Exposure index parameters.

Parameters	Description	Units
Flooded farmland	Extent of flooded farmlands	*%*
Houses destroyed	Number of houses destroyed by flooding	-
Inaccessibility	Number of roads, health centers, and schools flooded	-

Also, in the IPCC AR5, "*Vulnerability*" refers to the inherent characteristics of exposed elements and the systems in which they are embedded (e.g., the vulnerability of populations and their immediate environment in a village located within a flood-prone area) that can increase or, in some cases, reduce the potential consequences of a specific climatic hazard. Vulnerability comprises two key dimensions: "*Sensitivity*" and "*Capacity*".

- ***Sensitivity***: is determined by factors that directly influence the consequences of a hazard. It may include the physical attributes of a system (e.g., the construction materials of houses or the type of soil used for agriculture) as well as its social, economic, and cultural attributes (e.g., income structure, age distribution, or education level). In this study, the sensitivity indicator was developed based on both natural and socioeconomic parameters, including: 1) the distance from the village center to the main river, 2) the Strahler stream order, 3) population density, 4) the number of water entry points into the village, and 5) the poverty index. Based on expert judgment, these parameters were assigned weights of 30%, 30%, 15%, 15%, and 10%, respectively, to compute a composite indicator used to assess the degree of sensitivity of each village (Table 4). Higher weights were assigned to the distance from the village to the river and the Strahler stream order, as these factors are closely linked to flood occurrence and its significance, compared to the other sensitivity indices.
- ***Capacity***: in the context of climate risk assessment, refers to the ability of societies and communities to prepare for and respond to current and future climate impacts. It consists of two interrelated components.

- ***Coping capacity***: the ability of individuals, institutions, organizations, and systems to respond effectively to and recover from adverse situations in the short to medium term, drawing upon their skills, values, beliefs, resources, and available opportunities (e.g., the establishment of early warning systems). In the present study, the existence and effective implementation of a contingency plan during flood crises, as well as the presence or absence of water level monitoring markers, were considered as key adaptive capacity indicators (Table 5).
- ***Adaptive capacity***: the ability of systems, institutions, humans, and other organisms to adjust to potential damage, take advantage of opportunities, or respond to consequences. In this study, the actions undertaken before and during flood periods, as reported during the interviews, were used to assess the adaptive capacity of the populations in the surveyed villages (Table 6).

Table 4. Sensitivity index parameters.

Parameters	Description	Units
Distance	Distance from the village center to the main river	*m*
Water entry points	Number of water entry points into the village	-
Stream Order	Strahler stream order	-
Poverty index	Commune poverty index in which the village is located	-
Density	Population density of the subdistrict of the village	$Persons/km^2$

Table 5. Coping capacity index parameters.

Parameters	Description	Units
Contingency plan	Existence and implementation of contingency plan	-
Water level monitoring	Existence of water level monitoring markers	-

Table 6. Adaptive capacity index parameters.

Parameters	Description	Units
Early harvesting	Practice of early harvesting to reduce flood losses	-
Water drainage	Indigenous techniques for floodwater removal	-
Relocation	Relocation to safe areas during flood events	-

2.2.3. Flood Risk Assessment

- *Normalization of Indicators*

The normalization of indicators was carried out using the following formula (Equation (5)), in which a maximum weight of 1 is assigned to the highest raw value of the indicator (Max_Ind_i), while a minimum weight of 0 is assigned to the lowest raw value of the indicator (Min_Ind_i)

$$VN_i = \frac{X_i - Min\_Ind_i}{Max\_Ind_i - Min\_Ind_i} \tag{5}$$

where VN_i represents the normalized value of indicator Ind_i This transformation scales all indicator values between 0 and 1, facilitating their comparison and integration into the composite risk index.

- *Weighting and Aggregation of Indicators*

The weighting of indicators was performed using the budget allocation method, also known as the "pebble method." This approach is considered semi-objective, as it relies on expert judgment to assign relative importance to each indicator. In practice, a total of ten pebbles was distributed among the indicators according to their perceived significance, with a higher number of pebbles representing greater importance. The experts emerged as community leaders in each commune after explaining the significance of each indicator to them.

The aggregation of indicators followed the Weighted Arithmetic Aggregation method, as recommended in the Vulnerability Assessment Reference Guide [10]. This method is widely used due to its simplicity, transparency, and ease of interpretation. To calculate the composite indicator (CI) for each component of risk, the individual indicators were multiplied by their respective weights, summed, and then divided by the total sum of all weights, as expressed in the following formula (Equation (6))

$$CI = \frac{\left(I_1 * w_1 + I_2 * w_2 + \cdots + I_n * w_n\right)}{w_1 + w_2 + \cdots + w_n} \tag{6}$$

In this formula, CI represents the composite indicator, such as sensitivity; I denotes an individual indicator of a risk component, for example, the distance of the village from the river; and w corresponds to the weight assigned to that indicator. The maximum normalized values of the hazard indicators for each village particularly those related to maximum observed water levels and flood duration were considered representative of the hazard (or danger) component for the respective village. The average of these indicators was used, reflecting the nature of these variables, which capture the peak intensity of flooding within each locality.

- *Computation of Vulnerability Indicators*

For the vulnerability component, a weighted average of the corresponding indicators was calculated and taken as representative of the sensitivity subcomponent. Indeed, the two quantified sensitivity indicators namely, the distance of the village from the main river and the number of water entry points contribute to vulnerability at different degrees of influence.

The average of the indicators representing the subcomponents coping capacity and adaptive capacity was calculated and considered as representative of the overall adaptive capacity component.

Vulnerability indicator was then derived by combining sensitivity and adaptive capacity (Equation (7)). It is important to note that these two components exert opposite effects on vulnerability: an increase in sensitivity leads to higher vulnerability, whereas an increase in adaptive capacity contributes to reducing it.

$$\text{Vulnerability} = \frac{\text{Sensitivity} + (1 - \text{Adaptative capacity})}{2} \quad (7)$$

- *Computation of Risk Indicators*

The flood risk indicator was carried out using the weighted arithmetic mean to combine the three components of risk. Accordingly, the following formula was applied (Equation (8)):

$$\text{Risk} = \frac{(\text{Hazard} * W_H) + (\text{Vulnerability} * W_V) + (\text{Exposure} * W_E)}{W_H + W_V + W_E} \quad (8)$$

where W is the weighting coefficient assigned to each risk component. The risk levels were then categorized based on their metric values ranging from 0 to 1, which were subsequently transformed into categorical values on a five-level scale (1 to 5) to facilitate interpretation and description of the different levels of flood risk (Table 7).

Table 7. Categorization of risk levels.

Indicators range of values	Category	Description
0 - 0.2	1	Very Low
>0.2 - 0.4	2	Low
>0.4 - 0.6	3	Moderate
>0.6 - 0.8	4	High
>0.8 - 1	5	Very High

Adapted from GIZ Risk assessment guide [11].

3. Results

3.1. Characteristics of the Interviewed Population

This section presents the socio-demographic characteristics of the interviewed population, including variables such as age, gender, occupation, education level, and household size. Table 8 presents the indicator dictionary used for the village-level flood risk survey. It lists and defines all parameters measured during data collection, including demographic, socioeconomic, and flood-impact variables.

Table 8. Indicator dictionary for the village-level survey.

Parameters	Description
Villages (N)	Total number of interviewed villages per commune
Respondents (N)	Total number of valid questionnaires per village
Women (%)	Share of female respondents
Average Age (years)	Mean age of respondents
Median HH Size	Median number of people per household
Poverty Index (%)	Poverty Index
Illiteracy Rate (%)	Share of respondents who cannot read and write
Farming HH (%)	Share of households relying mainly on agriculture
Distance to River (m)	Median distance from the household to the nearest water body
Flood Depth 2024 (cm)	Median water depth inside houses during the 2024 flood
Flood Duration (days)	Median number of days households were flooded
Access to EWS (%)	Share of households receiving flood alerts (SMS, radio, town crier)
Warned Before Last Flood (%)	Share of households warned before the last flood event
Houses Damaged (%)	Share of households reporting damage to their head of village
Crops Lost (%)	Share of households reporting crop losses
Livestock Lost (%)	Share of households reporting livestock losses
Water Contamination (%)	Share of households reporting contaminated water sources
HH Protection Measures (%)	Share of households taking at least one protective action [a]
Assistance received (%)	Share of households that received any form of support [b]

a. Protective actions: elevating assets, moving livestock, early harvesting, household relocation to safe areas, etc.; b. Support (financial, material, or technical) from government, NGOs, or community groups in response to flood events.

Each indicator describes a specific aspect of household vulnerability, exposure, preparedness, and response ranging from basic characteristics (e.g., household size, literacy rate) to flood related factors (e.g., flood depth, duration, damage, assistance received). This table ensures clarity and consistency in interpreting the survey data.

Table 9 summarizes the key findings of the village-level social survey on flood risk across communes. The results show significant variability in socioeconomic conditions and exposure to floods. Most households rely on agriculture and experience high poverty and illiteracy rates, particularly in Aguégués, Sô-Ava, and Adjohoun. The average household size ranges from four to six members, reflecting the relatively large family structures typical of rural communities. The average age of respondents varies between 33 and 55 years, indicating a predominantly active working population. The median distance to the nearest river ranges from 50 to 500 meters, while flood depths (100 - 250 cm) and durations (up to 90 days) differ across communes, often resulting in recurrent damage to houses, crops, and livestock. Access to early warning systems and protective measures remains limited in many villages, although some households reported receiving assistance and community support. Overall, the socioeconomic survey highlights significant disparities in vulnerability and adaptive capacity among villages and communes within the study area.

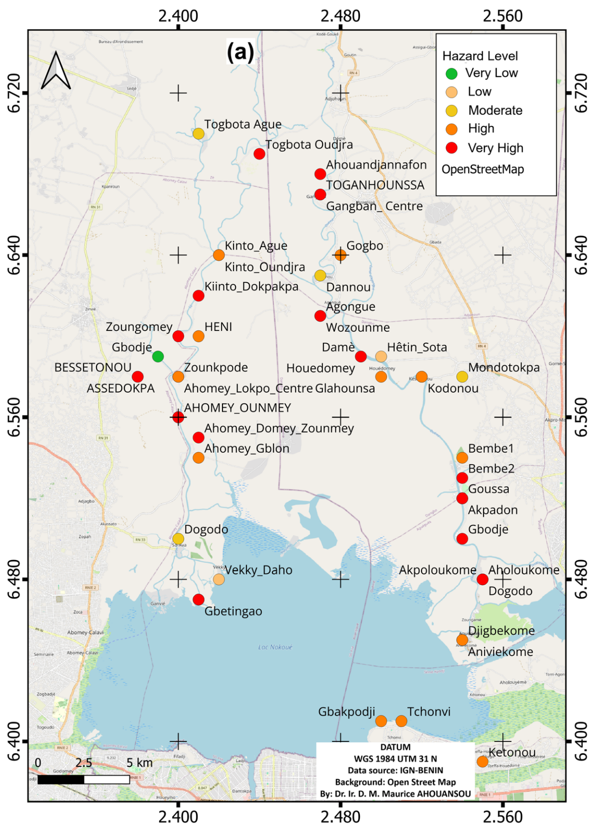
Table 9. Indicator dictionary for the village-level survey.

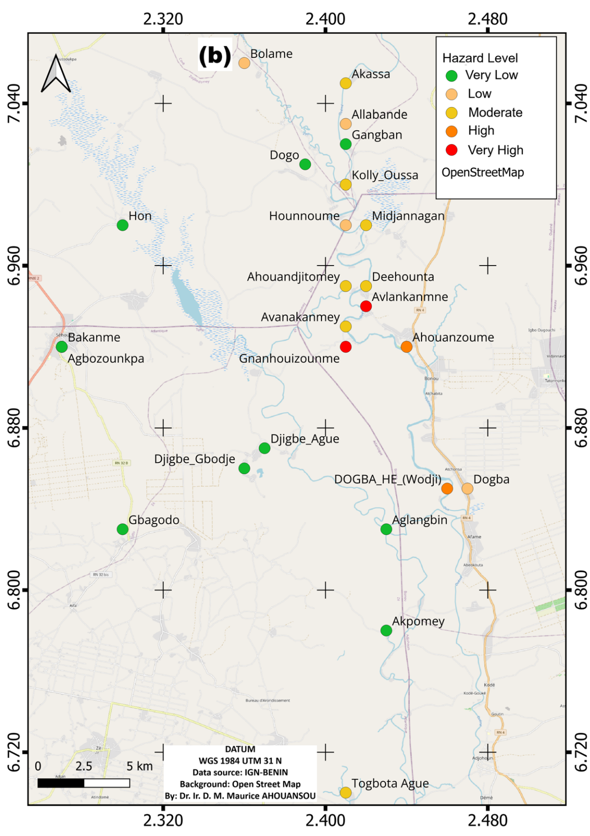
Parameters	Abomey -Calavi	Adjo -houn	Agué -gués	Bonou	Dangbo	Ouinhi	S'emè -Kpodji	Sô -Ava	Toffo	Zagna -nado	Zê	Zogbo -domey	Total
Villages (N)	1	7	10	6	8	6	3	17	5	12	5	9	**89**
Respondents (N)	5	35	50	30	40	30	15	85	25	60	25	45	**445**
Women (%)	20	35.6	48.3	36.4	26	36.8	44	38	41	32	38	46	-
Average Age (years)	32.6	45.7	46.5	33.8	35.6	41.5	39.3	55.2	46.3	52.1	48.2	46.1	-
Median HH Size	4	6.2	5.3	5.6	5.2	5.5	6.2	5.3	4.8	6.2	5.8	6.4	-
Poverty Index (%)	43	57	50	50	50	96	50	43	43	96	96	96	-
Illiteracy Rate (%)	80.0	85.0	75.1	83.7	52.2	70.5	85.0	73.0	84.0	82.0	88.0	86.0	-
Farming HH (%)	100	100	100	100	100	100	100	100	100	100	100	100	-
Distance to River (m)	150	120	30	100	150	150	100	50	500	200	300	400	-
Flood Depth 2024 (cm)	250	200	200	150	150	150	200	150	50	200	200	150	-
Flood Duration (days)	120	90	90	90	90	90	90	90	30	90	90	90	-
Access to EWS (%)	20	37.1	36.0	26.7	17.5	13.3	24	22.35	0.0	11.1	24.0	15.5	-
Warned Before Last Flood (%)	20	22.8	28.0	36.0	30.0	40.0	20.0	41.2	16.0	33.3	20.0	22.2	-
Houses Damaged (%)	60.0	42.8	40.0	37	37.5	33.3	46.7	41.2	0.0	46.7	20.0	11.1	-
Crops Lost (%)	100	100	100	100	100	100	100	100	100	100	100	100	-
Livestock Lost (%)	100	85.7	80.0	83.3	75.5	83.3	33.3	100	0.0	50.0	40	11.1	-
Water Contamination (%)	80.0	80.0	76.0	67.0	70.0	100	53.3	82.3	40.0	50.0	48.0	55.5	-
HH Protection Measures (%)	100	85.7	100	93.0	100	100	80.0	100	60.0	83.3	80.0	77.8	-
Assistance received (%)	60	28.6	50.0	20.0	25.0	17.0	33.3	41.2	0.0	50.0	20.0	27.0	-

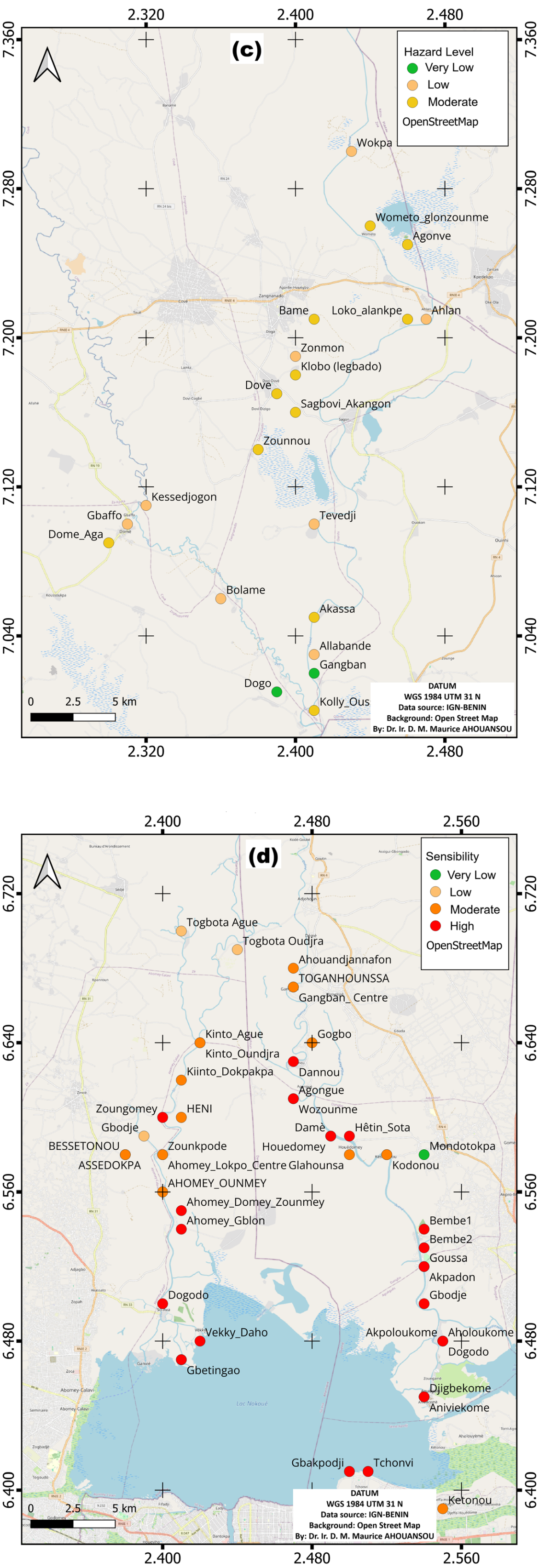
3.2. Level of Flood Hazard and Sensitivity across Villages

Figures 2(a)-(c) show the spatial distribution of villages according to the degree of flood hazard resulting from the overflow of the Oueme River and its tributaries.

The hazard indicators were calculated after normalizing the maximum water levels observed during flood periods and the duration of inundation in each village. The results indicate that 21 villages have a very high degree of exposure to floods, 22 villages are highly exposed, 24 villages are moderately exposed, and 19 villages are slightly exposed. It should be noted that more than 75.3% of the surveyed villages have an exposure level ranging from moderate to very high (**Table 10**).


(a)
Hazard Level
Very Low
Low
Moderate
High
Very High
OpenStreetMap
Togbota Ague
Togbota Oudjra
Ahouandjannafon
TOGANHOUNSSA
Gangban_Centre
Kinto_Ague
Gogbo
Kinto_Oundjra
Dannou
Kiinto_Dokpakpa
Agongue
Wozounme
Zoungomey
HENI
Gbodje
Damè
Hêtin_Sota
BESSETONOU
Zounkpode
Houedomey
Mondotokpa
ASSEDOKPA
Ahomey_Lokpo_Centre
Glahounsa
Kodonou
AHOMEY_OUNMEY
Ahomey_Domey_Zounmey
Ahomey_Gblon
Bembe1
Bembe2
Goussa
Akpadon
Gbodje
Dogodo
Vekky_Daho
Akpoloukome
Aholoukome
Dogodo
Gbetingao
Djigbekome
Aniviekome
Gbakpodji
Tchonvi
Ketonou
DATUM
WGS 1984 UTM 31 N
Data source: IGN-BENIN
Background: Open Street Map
By: Dr. Ir. D. M. Maurice AHOUANSOU
0 2.5 5 km
2.400 2.480 2.560
6.720 6.640 6.560 6.480 6.400


(b)
Hazard Level
Very Low
Low
Moderate
High
Very High
OpenStreetMap
Bolame
Akassa
Allabande
Gangban
Dogo
Kolly_Oussa
Hon
Hounnoume
Midjannagan
Ahouandjitomey
Deehounta
Avlankanmne
Avanakanmey
Bakanme
Ahouanzoume
Agbozounkpa
Gnanhouizounme
Djigbe_Ague
Djigbe_Gbodje
DOGBA_HE_(Wodji)
Dogba
Gbagodo
Aglangbin
Akpomey
Togbota Ague
DATUM
WGS 1984 UTM 31 N
Data source: IGN-BENIN
Background: Open Street Map
By: Dr. Ir. D. M. Maurice AHOUANSOU
0 2.5 5 km
2.320 2.400 2.480
7.040 6.960 6.880 6.800 6.720



(c)
2.320
2.400
2.480
7.360
7.280
7.200
7.120
7.040
Hazard Level
Very Low
Low
Moderate
OpenStreetMap
Wokpa
Wometo_glonzounme
Agonve
Bame
Loko_alankpe
Ahlan
Zonmon
Klobo (legbado)
Dove
Sagbovi_Akangon
Zounnou
Kessedjogon
Gbaffo
Dome_Aga
Tevedji
Bolame
Akassa
Allabande
Gangban
Dogo
Kolly_Ous
0 2.5 5 km
DATUM
WGS 1984 UTM 31 N
Data source: IGN-BENIN
Background: Open Street Map
By: Dr. Ir. D. M. Maurice AHOUANSOU
(d)
2.400
2.480
2.560
6.720
6.640
6.560
6.480
6.400
Sensibility
Very Low
Low
Moderate
High
OpenStreetMap
Togbota Ague
Togbota Oudjra
Ahouandjannafon
TOGANHOUNSSA
Gangban_ Centre
Kinto_Ague
Gogbo
Kinto_Oundjra
Kiinto_Dokpakpa
Dannou
Agongue
Zoungomey
HENI
Wozounme
Gbodje
Damè
Hêtin_Sota
BESSETONOU
Zounkpode
Houedomey
Mondotokpa
ASSEDOKPA
Ahomey_Lokpo_Centre
Glahounsa
Kodonou
AHOMEY_OUNMEY
Ahomey_Domey_Zounmey
Ahomey_Gblon
Bembe1
Bembe2
Goussa
Akpadon
Gbodje
Dogodo
Vekky_Daho
Akpoloukome
Aholoukome
Dogodo
Gbetingao
Djigbekome
Aniviekome
Gbakpodji
Tchonvi
Ketonou
0 2.5 5 km
DATUM
WGS 1984 UTM 31 N
Data source: IGN-BENIN
Background: Open Street Map
By: Dr. Ir. D. M. Maurice AHOUANSOU

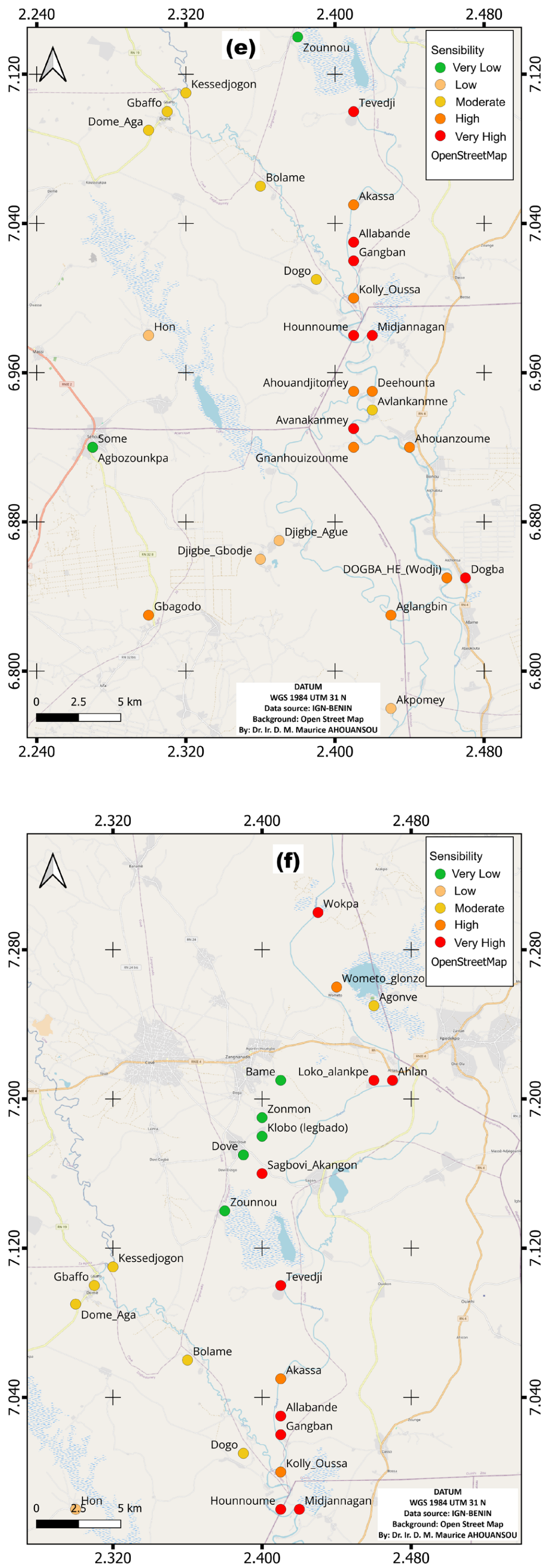
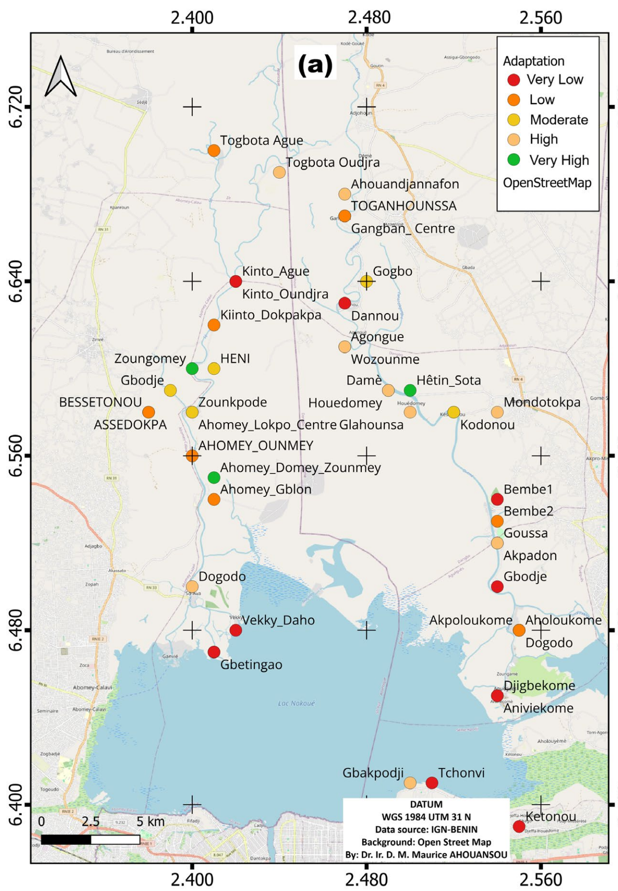


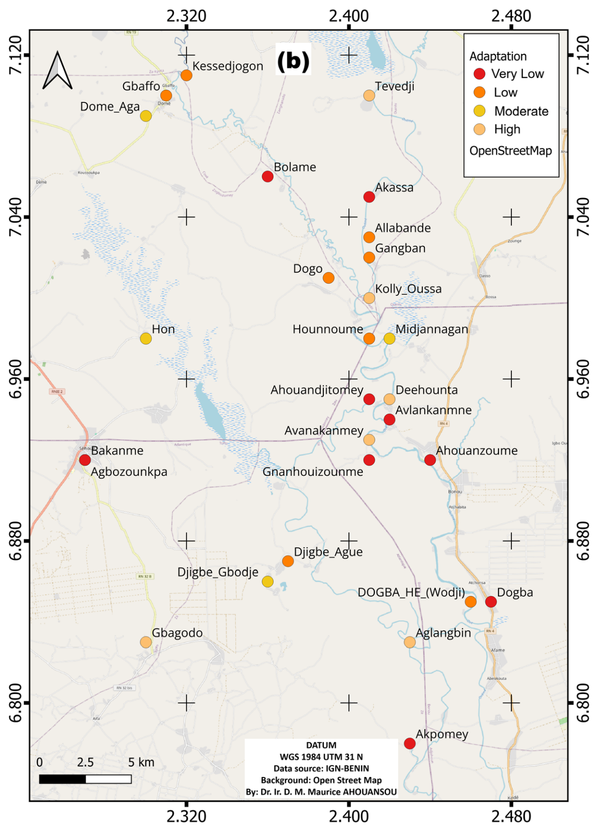
Figure 2. Mapping of village exposure levels to flooding (a-c) and distribution of villages according to their degree of sensitivity to flooding (d-f): (a, d) Villages located in the southern part of the study. (b, e) Villages located in the central part of the study area. (c, f) Villages located in the northern part of the study area.

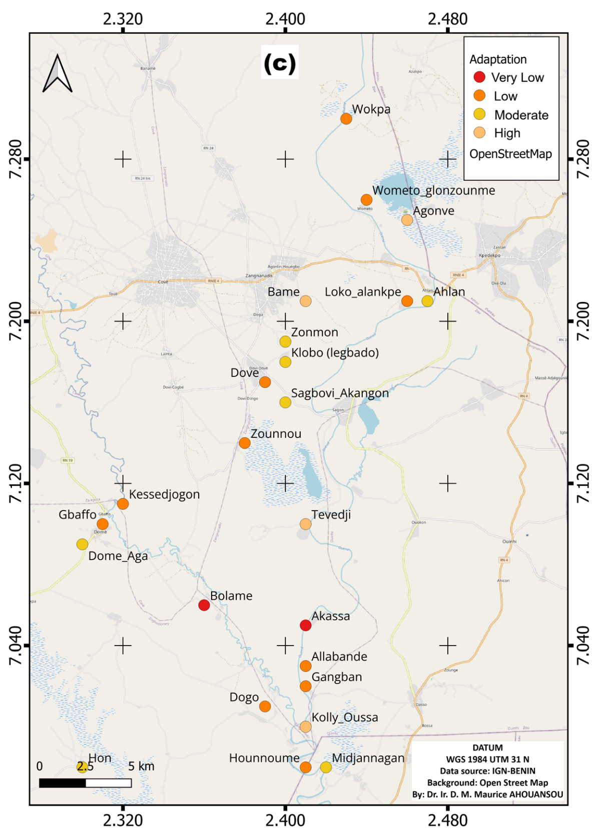
Table 10. Categorization of hazard levels.

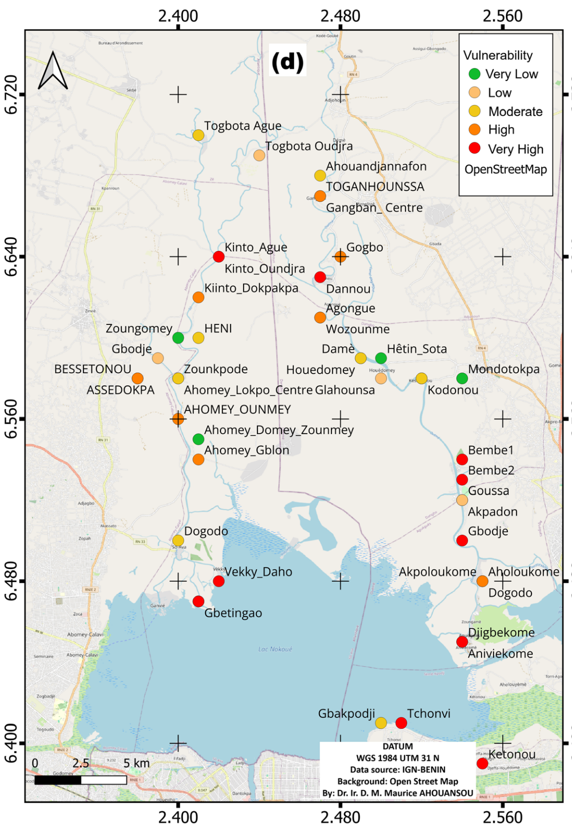
Hazard level	Indicators	Number of villages
Very Low	0.0 - 0.40	3
Low	0.41 - 0.56	19
Moderate	0.57 - 0.70	24
High	0.71 - 0.80	22
Very High	0.81 - 1.00	21
Total	-	**89**

In addition, after computing the composite indicator used to of the degree of sensitivity of each village, it has been found out that 20 villages fall within the very high sensitivity class and 17 within the high sensitivity class, indicating that a large proportion of villages are highly susceptible to flood impacts. In contrast, only 14 villages are classified as very low sensitivity, while 19 are low and another 19 moderates, reflecting spatial disparities in vulnerability linked to proximity to rivers, topography, and socioeconomic conditions (Table 11). Figures 2(d)-(f) show the spatial distribution of villages according to the degree of their sensitivity to flooding by the overflow of the Oueme River and its tributaries.




(b)
Adaptation
Very Low
Low
Moderate
High
OpenStreetMap
Kessedjogon
Gbaffo
Dome_Aga
Tevedji
Bolame
Akassa
Allabande
Gangban
Dogo
Kolly_Oussa
Hon
Hounnoume
Midjannagan
Ahouandjitomey
Deehounta
Avlankanmne
Avanakanmey
Bakanme
Agbozounkpa
Gnanhouizounme
Ahouanzoume
Djigbe_Ague
Djigbe_Gbodje
DOGBA_HE_(Wodji)
Dogba
Gbagodo
Aglangbin
Akpomey
DATUM
WGS 1984 UTM 31 N
Data source: IGN-BENIN
Background: Open Street Map
By: Dr. Ir. D. M. Maurice AHOUANSOU
0 2.5 5 km
2.320 2.400 2.480
7.120 7.040 6.960 6.880 6.800


(c)
Adaptation
Very Low
Low
Moderate
High
OpenStreetMap
Wokpa
Wometo_glonzounme
Agonve
Bame
Loko_alankpe
Ahlan
Zonmon
Klobo (legbado)
Dove
Sagbovi_Akangon
Zounnou
Kessedjogon
Gbaffo
Dome_Aga
Tevedji
Bolame
Akassa
Allabande
Gangban
Dogo
Kolly_Oussa
Hon
Hounnoume
Midjannagan
DATUM
WGS 1984 UTM 31 N
Data source: IGN-BENIN
Background: Open Street Map
By: Dr. Ir. D. M. Maurice AHOUANSOU
0 2.5 5 km
2.320 2.400 2.480
7.280 7.200 7.120 7.040


(d)
Vulnerability
Very Low
Low
Moderate
High
Very High
OpenStreetMap
2.400
2.480
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6.720
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6.560
6.480
6.400
Togbota Ague
Togbota Oudjra
Ahouandjannafon
TOGANHOUNSSA
Gangban_ Centre
Kinto_Ague
Kinto_Oundjra
Gogbo
Kiinto_Dokpakpa
Dannou
Agongue
Zoungomey
HENI
Wozounme
Gbodje
Damè
Hêtin_Sota
BESSETONOU
Zounkpode
Houedomey
Mondotokpa
ASSEDOKPA
Ahomey_Lokpo_Centre
Glahounsa
Kodonou
AHOMEY_OUNMEY
Ahomey_Domey_Zounmey
Ahomey_Gblon
Bembe1
Bembe2
Goussa
Akpadon
Gbodje
Dogodo
Vekky_Daho
Akpoloukome
Aholoukome
Dogodo
Gbetingao
Djigbekome
Aniviekome
Gbakpodji
Tchonvi
Ketonou
0
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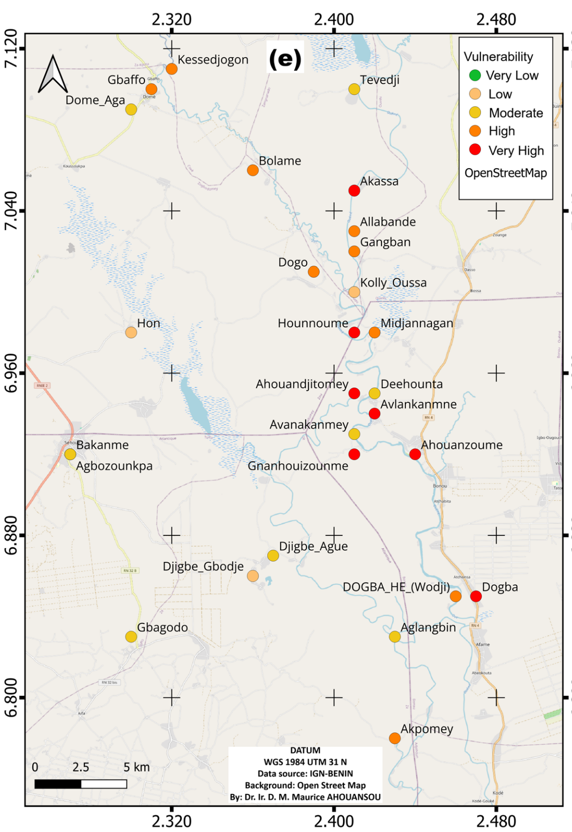
5 km
DATUM
WGS 1984 UTM 31 N
Data source: IGN-BENIN
Background: Open Street Map
By: Dr. Ir. D. M. Maurice AHOUANSOU


(e)
Vulnerability
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Low
Moderate
High
Very High
OpenStreetMap
2.320
2.400
2.480
7.120
7.040
6.960
6.880
6.800
Kessedjogon
Gbaffo
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Bolame
Akassa
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Gangban
Dogo
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Hon
Hounnoume
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Deehounta
Avlankanmne
Avanakanmey
Bakanme
Agbozounkpa
Gnanhouizounme
Ahouanzoume
Djigbe_Ague
Djigbe_Gbodje
DOGBA_HE_(Wodji)
Dogba
Gbagodo
Aglangbin
Akpomey
0
2.5
5 km
DATUM
WGS 1984 UTM 31 N
Data source: IGN-BENIN
Background: Open Street Map
By: Dr. Ir. D. M. Maurice AHOUANSOU

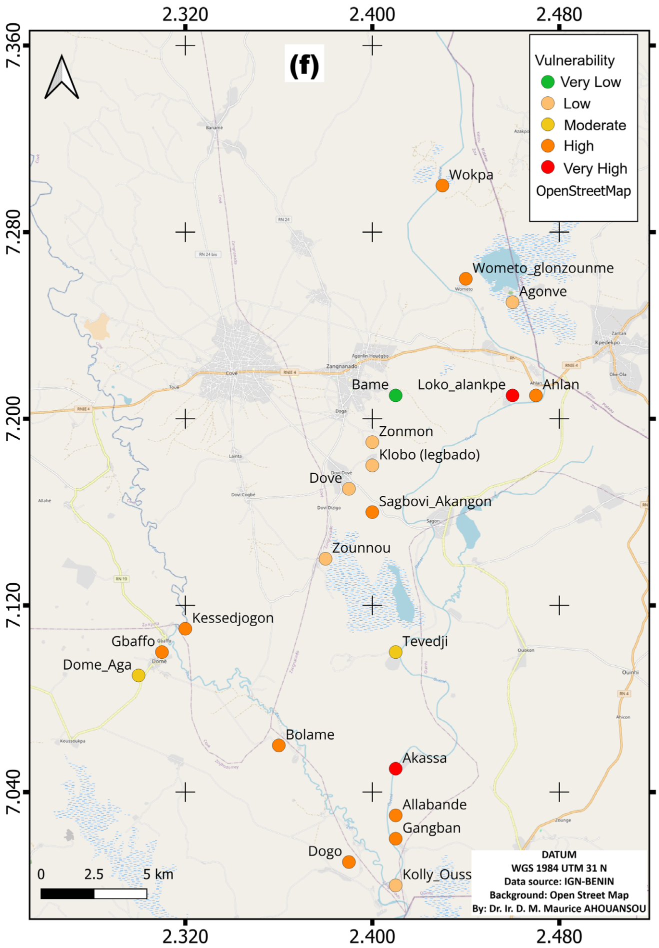


Figure 3. Spatial mapping of village adaptation levels to flooding (a-c) and distribution of villages according to their degree of vulnerability to flooding (d-f): (a, d) Villages located in the southern part of the study. (b, e) Villages located in the central part of the study area. (c, f) Villages located in the northern part of the study area.

Table 11. Categorization of sensitivity levels.

Sensitivity level	Indicators	Number of villages
Very Low	0.0 - 0.10	14
Low	0.10 - 0.25	19
Moderate	0.25 - 0.50	19
High	0.50 - 0.75	17
Very High	0.75 - 1.0	20
Total	-	**89**

3.3. Level of Adaptation and Vulnerability to Flooding

The average level of adaptation was calculated as the simple mean of two key indicators: the index of mechanisms and the actions undertaken before and during flood periods. This adaptive capacity reflects the degree of preparedness of residents in each village to cope with the adverse effects of flooding. In this regard, the village of Tohouès stands out as the most capable of managing and responding effectively to flood impacts.

Conversely, 60 villages were identified as having low to very low adaptive mechanisms, indicating limited preparedness and a higher susceptibility to flood-related damages (Table 12). Figures 3(a)-(c) illustrate the spatial distribution of villages according to their degree of adaptive capacity to flooding caused by the overflow of the Ouémé River and its tributaries.

Table 12. Categorization of adaptation levels.

Adaptation level	Indicators	Number of villages
Very High	0.0 - 0.13	1
High	0.13 - 0.33	5
Moderate	0.33 - 0.57	22
Low	0.57 - 0.67	34
Very Low	0.67 - 1.0	26
Total	-	**89**

In addition, the vulnerability indices of the villages were determined by calculating the complementary average of the adaptation capacity indices (1 – adaptive capacity) and the potential impact indices. These vulnerability indices provide a quantitative measure that characterizes the susceptibility of each village to flood hazards. The analysis reveals that 25 villages are highly predisposed to experience severe flood-related damage due to their high vulnerability scores. In contrast, only 10 villages show lower levels of vulnerability, suggesting relatively greater resilience to flood impacts compared to the others (Table 13).

Table 13. Categorization of vulnerability levels.

Vulnerability level	Indicators	Number of villages
Very Low	0.0 - 0.13	10
Low	0.13 - 0.28	12
Moderate	0.28 - 0.44	22
High	0.44– 0.65	20
Very High	0.65 - 0.86	25
Total	-	**89**

This variation highlights the uneven spatial distribution of vulnerability within the study area, reflecting differences in exposure, adaptive capacity, and socioeconomic conditions among the villages.

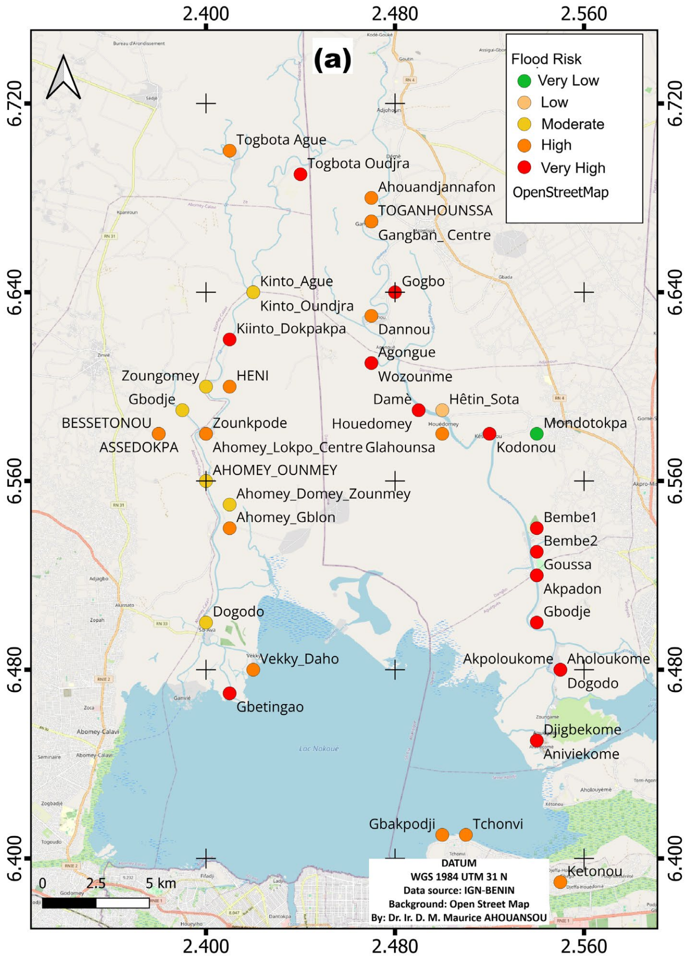
3.4. Level of Risk to Flooding

The flood risk indices of the villages were computed by averaging the hazard, vulnerability, and exposure indices. These composite indices provide a quantitative representation of the overall flood risk profile of each village.

Table 14 presents the classification of villages according to their flood risk levels based on the calculated indicators.

Table 14. Categorization of flood risk levels.

Flood Risk level	Indicators	Number of villages
Very Low	0.3 - 0.39	5
Low	0.40 - 0.56	9
Moderate	0.57 - 0.64	25
High	0.65 - 0.72	40
Very High	0.73 - 0.86	10
Total	-	**89**



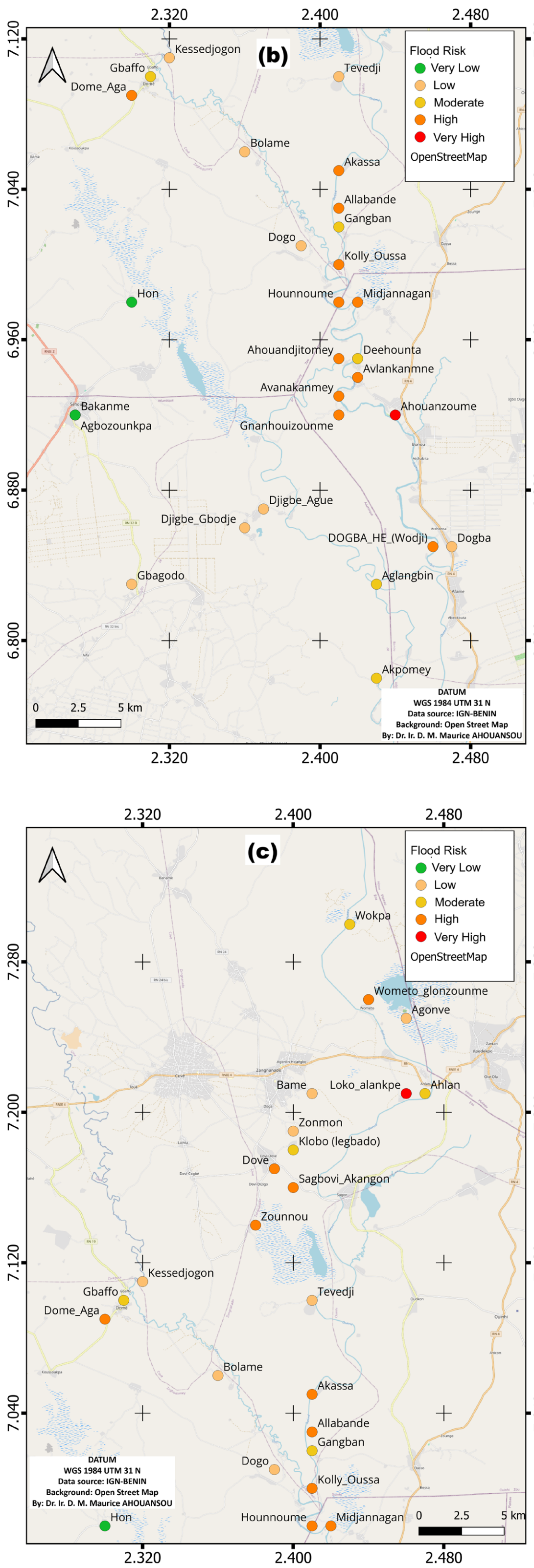


Figure 4. Mapping of village Flood Risk levels: (a) Villages located in the southern part of the study. (b) Villages located in the central part of the study area. (c) Villages located in the northern part of the study area.

The results reveal that the majority of villages fall within the high and moderate risk categories, comprising 40 and 25 villages respectively, which indicates that a substantial portion of the study area is highly exposed to flood hazards. In contrast, only about 15% of the villages (5 classified as very low and 9 as low) show reduced flood risk levels, while 10 villages fall into the very high-risk category, representing the most critical zones where flood impacts are likely to be most severe. Overall, the spatial distribution demonstrates a predominance of elevated flood risk across the region, primarily driven by variations in exposure, vulnerability, and adaptive capacity among villages. This highlights the urgent need for targeted adaptation and mitigation measures to enhance the resilience of the most vulnerable communities. **Figures 4(a)-(c)** illustrate the spatial distribution of villages according to their level of Flood risk caused by the overflow of the Oueme River and its tributaries.

In summary, the application of the proposed methodology for assessing flood risk levels in the Lower Ouémé River Basin revealed that both social vulnerability and overall flood risk are extremely high across the surveyed area. Among the 89 villages analyzed, several recorded risk index values approaching the maximum threshold of 1, indicating a critical level of exposure and limited adaptive capacity. This implies that approximately 57 % of the population affected by floodwaters is likely to experience severe damage in the event of a dam failure or major overflow. These findings underscore the high susceptibility of communities in the Lower Ouémé Valley and the urgent need for proactive risk management and adaptation strategies to reduce potential flood impacts.

4. Discussion

Promoting a culture of prevention is fundamental to reducing the impacts of disasters, safeguarding livelihoods, and, above all, protecting human lives (Armenakis et al., 2017; Tascón-González et al., 2020). Achieving this objective requires a comprehensive and systematic assessment of the multiple dimensions of risk within a given territory. In this study, particular attention is given to the social dimension of flood risk at the community level. The proposed methodology integrates the components of hazard, sensitivity, adaptive capacity, and vulnerability in line with the AR5 IPCC framework for risk analysis. Flood risk was assessed not only by considering the physical aspects of flooding—such as water-level rise and inundation extent, but also by evaluating the potential impacts on populations and critical infrastructure (Tascón-González et al., 2020). This integrated approach, based on composite risk indices, provides standardized and comparable results that support all stages of the disaster risk management cycle, including prevention, preparedness, response, and recovery. Ultimately, it enables a more objective evaluation of spatial and temporal flood risk patterns, thereby informing targeted adaptation and mitigation strategies.

According to the results, the hazard indicators with the greatest influence on increasing community exposure are flood depth and flood duration. These parameters represent a novel contribution to this type of analysis, as very few previous studies have incorporated them into the assessment of social exposure levels to flood risk. The spatial distribution of villages according to their degree of flood hazard, as indicated in **Figures 2(a)-(c)**, reveals a critical pattern of vulnerability in the study area. The normalization of maximum water levels and inundation duration as hazard indicators is a well-established approach for quantifying flood exposure, capturing both intensity and persistence dimensions of flood events (Mostafiz et al., 2022). The classification results 21 villages with very high exposure, 22 highly exposed, 24 moderately exposed, and 19 slightly exposed—demonstrate that over 75% of surveyed villages face moderate to very high flood hazard. Such a predominance of elevated exposure is consistent with findings in other riverine floodplain studies that highlight the clustering of vulnerable settlements along major water bodies and tributaries due to socio-economic factors and geographical constraints (Bossa et al., 2024; Handyastono et al., 2025). The repercussions of living in high flood hazard zones are profound, impacting livelihoods, health, and local development. Studies in similar rural contexts reveal that flood exposure significantly reduces household income, especially farming income, while increasing expenditures on health and food due to flood-induced damages and disruptions (Ashikbayeva et al., 2020). This underscores the importance of integrating flood hazard assessments with socio-economic vulnerability analysis for comprehensive risk management. The spatial distribution maps provide critical information for targeted interventions, as prioritizing villages with very high and high exposure can optimize resource allocation for flood mitigation, early warning, and resilience-building measures (Chen, 2022). Then, the spatial analysis of flood hazard exposure in this study aligns with broader research emphasizing the value of normalized water level and inundation duration metrics, the concentration of vulnerability in floodplain villages, and the socio-economic impacts of such exposure. These insights form a vital basis for planning flood risk reduction strategies tailored to the most affected communities.

The analysis of village sensitivity to flooding in the study area reveals notable spatial disparities in vulnerability. The finding that 20 villages fall within the very high sensitivity class and 17 within the high sensitivity class indicates a substantial proportion of villages are highly susceptible to flood impacts. This aligns with flood vulnerability studies in the Ouémé Basin, where proximity to rivers, topography, and socio-economic conditions significantly shape flood sensitivity (Tiepolo et al., 2019). Such factors consistently explain heightened vulnerability to flooding in riverine communities across West Africa (Tiepolo et al., 2019; Tingsanchali, 2012).

Conversely, the classification of some villages within very low to moderate sensitivity levels reflects heterogeneity in flood resilience and adaptive capacity. This pattern is observed globally, where spatial variability in elevation, river distance, and socio-economic assets create diverse sensitivity landscapes (Aznar-Crespo et al., 2021; Jabeen et al., 2010). Studies emphasize that socio-economic dimensions are key to understanding sensitivity beyond physical exposure alone, as poverty, education levels, and infrastructure influence community flood impacts. The spatial distribution maps (**Figures 2(d)-(f)**) facilitate focused flood risk management by pinpointing highly sensitive villages requiring prioritized intervention. This approach aligns with current best practices that integrate GIS-based hazard mapping with socio-economic data to optimize disaster resilience strategies (Skilodimou et al., 2021; Tomar et al., 2021). In conclusion, the village sensitivity analysis highlights the need for integrated flood risk assessments combining natural hazard data and socio-economic factors to tailor effective risk reduction in flood-prone river basins like Oueme.

The assessment of adaptive capacity among villages along the Oueme River provides critical insight into their preparedness to manage and respond to flood impacts. Calculating the average adaptation level using both pre-flood mechanisms and actions during flooding offers a comprehensive measure of village readiness, aligning with established frameworks for evaluating community adaptive capacity to hydrological hazards (Cutter et al., 2008; Few, 2003). The standout example of Tohouès village as the most capable in flood response highlights the role that localized knowledge, social organization, and resource availability play in effective adaptation (Birkmann, 2006). The finding that 60 villages display low to very low adaptive capacity is consistent with numerous studies in flood-prone regions, which demonstrate that limited adaptive mechanisms greatly increase susceptibility to flood damage and loss (Haque et al., 2023; Tingsanchali, 2012).Such limited preparedness is often associated with economic constraints, insufficient infrastructure, and lack of early warning and disaster education programs, factors commonly reported in rural West African contexts including Benin (Bossa et al., 2024).

Moreover, the calculation of vulnerability indices as a complement of adaptive capacity and potential impact indices follows best practices in flood vulnerability modeling, effectively integrating both exposure and resilience dimensions (Fekete, 2009). The identification of 25 highly vulnerable villages versus 10 with lower vulnerability underscores the critical spatial heterogeneity in flood risk, a characteristic frequently observed in river basin flood studies due to natural, social, and economic variability (Haque et al., 2023). The spatial distribution of vulnerability illustrated in **Figures 3(a)-(c)** emphasizes the need for differentiated flood risk management strategies that address specific local conditions and capacity levels. Targeted interventions in the most vulnerable villages could include infrastructure improvements, community-based early warning systems, and capacity-building programs aimed at enhancing adaptive capacity (Ahern et al., 2005).

In sum, this study's integration of adaptive capacity and impact assessments to derive vulnerability indices provides a robust framework for guiding flood risk reduction efforts in the Oueme floodplain, reinforcing the importance of enhancing adaptive capacities to reduce community vulnerability to flooding.

The computation of flood risk indices by averaging hazard, vulnerability, and exposure indices offers a holistic quantitative measure of overall flood risk in each village, consistent with established flood risk assessment methodologies (Bossa et al., 2024). This integrated approach aligns with multi-criteria analysis frameworks widely used in the field, such as the Analytical Hierarchy Process (AHP) combined with GIS, which facilitate precise weighting and spatial mapping of different flood risk components (Al-Omari et al., 2024; Aydin & Sevgi Birincioğlu, 2022; Rincón et al., 2018).

The results identifying 40 villages in the high-risk category and 25 in moderate risk reflect a significant spatial concentration of flood susceptibility, which corresponds to patterns observed in similar river basins where flooding is driven by natural and socio-economic factors like topography, land use, and population density (Kohno & Higuchi, 2023; Roccati et al., 2021). The presence of 10 villages in the very high-risk zone emphasizes areas where flood impacts may be most severe and where immediate mitigation and adaptation efforts should be prioritized.

The spatial distribution of flood risk as revealed emphasizes the need for differentiated flood management strategies that address variations in exposure, vulnerability, and adaptive capacity across communities. Targeted interventions can include structural measures such as improved flood defenses, alongside community-based preparedness and socio-economic resilience building, which together reduce the overall burden of flood disasters. Overall, this comprehensive risk profiling approach highlights the urgency for tailored flood adaptation and mitigation policies that enhance resilience of the most vulnerable villages in the Oueme River Basin, confirming the utility of integrated multi-dimensional flood risk assessments in guiding effective disaster risk reduction.

The spatial distribution of social risk through mapping has proven to be an effective approach for identifying villages most susceptible to flood hazards, thereby enabling a more accurate assessment and diagnosis of risk. For instance, combining a flood exposure map with a vulnerability map helps to pinpoint villages classified from high to very high risk, guiding the implementation of urgent and targeted interventions. Conducting such analyses at a detailed spatial scale is valuable not only for strengthening emergency response but also for enhancing preventive planning and community resilience. Furthermore, the increasing availability of open-access datasets provides a valuable resource for this type of research, although certain limitations persist, particularly regarding the subjectivity inherent in survey-based data.

To strengthen the practical relevance of the study, the findings can be translated into clear, actionable policy recommendations. Specifically, the flood-risk maps provide a robust decision-support tool for prioritizing public investment in the 10 villages classified as "very high risk." In these localities, infrastructure interventions should focus on the rehabilitation and elevation of critical assets such as roads, schools, health centers and water points, as well as the construction of small-scale flood protection works (e.g., drainage channels, raised platforms, or retention basins). In parallel, the spatialized risk information can inform the design of targeted, community-based early warning systems, by identifying optimal locations for installing hydrological gauges and rainfall sensors upstream of the most exposed settlements. These systems should be coupled with locally adapted communication mechanisms (community relays, local radio, etc.) and predefined response protocols co-developed with communities. More broadly, integrating the AR5-based risk maps into communal development plans and disaster risk management strategies would enhance anticipatory governance, enabling authorities to shift from reactive emergency response toward preventive and risk-informed adaptation planning.

This study has several limitations that should be acknowledge when interpreting the results. First, the flood risk assessment is based on a static representation of hazard, exposure and vulnerability, reflecting conditions at the time of data collection and therefore not capturing temporal dynamics such as seasonal variability, interannual climate variability, or future changes induced by climate change and land-use evolution. Second, the analysis relies partly on community-reported survey data regarding past flood events, which may be subject to recall bias and subjective perception, potentially affecting the accuracy of indicators related to flood frequency, duration and impacts. Third, the limited available of in situ hydrological and meteorological monitoring data restricted the calibration and validation of hazard-related indicators, which may influence the precision of risk classification in some villages. Despite these constraints, the adopted AR5-based, participatory spatial approach provides a robust baseline for local flood risk assessment and offers a foundation for future studies integrating dynamic modelling, long-term observations and high-resolution remote sensing data.

5. Conclusion

The present study assessed flood hazard, exposure, vulnerability, and risk levels in the Lower Ouémé River Basin using an integrated approach consistent with the IPCC AR5 framework. This methodology combined biophysical and socioeconomic parameters to provide a comprehensive understanding of how communities in the basin are affected by recurring floods. By incorporating indicators such as flood depth, flood duration, distance to rivers, water entry points, poverty index, and population density, the analysis captured both the natural and social dimensions of flood risk. The resulting indices were normalized and aggregated to derive spatially explicit maps of hazard, sensitivity, adaptive capacity, and vulnerability for 89 villages across the study area.

The results revealed considerable spatial disparities in exposure and vulnerability levels among villages. More than 72 % of the surveyed villages exhibited exposure levels ranging from moderate to very high, mainly due to their proximity to the Ouémé River and its tributaries, as well as the persistence of floods lasting over 90 days with depths reaching up to 250 cm. The sensitivity analysis showed that factors such as distance to the river and the number of water entry points into villages play a crucial role in determining flood susceptibility. The integration of socioeconomic parameters, including poverty and population density, further highlighted the unequal distribution of risk across the basin.

Adaptive capacity varied significantly from one community to another. The village of Tohouès demonstrated the strongest ability to cope with flood impacts, while approximately sixty villages exhibited weak to very weak adaptive mechanisms, reflecting limited preparedness and a high dependency on external support. The vulnerability index, derived from the combination of adaptive capacity and potential impacts, indicated that 25 villages are highly predisposed to severe flood damage, whereas only 10 showed relatively low vulnerability levels. The final composite risk index—calculated from hazard, exposure, and vulnerability components—confirmed that the majority of the study area falls under high to very high-risk categories.

Mapping the spatial distribution of these indices has proven to be an effective tool for identifying priority zones and supporting decision-making in disaster risk management. The combination of flood exposure and vulnerability maps provides a clear visual diagnosis of villages most in need of urgent interventions. Detailed-scale analyses enable better emergency planning, prevention strategies, and community-based adaptation actions. The inclusion of innovative indicators such as evacuation time also enhances the accuracy of vulnerability assessments and underscores the importance of human behavioral factors in flood risk reduction.

Overall, this study highlights the urgent need to strengthen local adaptation strategies, improve early warning systems, and promote a culture of prevention within flood-prone communities. The use of open-access datasets and participatory surveys demonstrates the feasibility of replicating this approach in other regions, though attention should be given to data quality and subjectivity. By integrating scientific analysis with local realities, the methodology developed here provides a valuable framework for policymakers and practitioners to design targeted interventions that enhance resilience and reduce the devastating impacts of floods in the Lower Ouémé Valley and similar riverine environments.

Acknowledgements

The authors would like to express their sincere gratitude to the DURAGIRE Program for its collaboration, provision of documentation, and financial support. Special thanks are extended to the local authorities and civil servants for their invaluable assistance in gathering field data, as well as to the team of experts who contributed to the application of the IPCC AR5 methodology. The authors also acknowledge the anonymous reviewers for their constructive comments and insightful suggestions, which greatly improved the quality of this paper.

Conflicts of Interest

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

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