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Flood risk modelling using the hierarchical process analysis (HPA) method: Example of the city of Thies, Senegal

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Abstract

Based on a pair-wise comparison of passive factors (the physical environment (slope, permeability, porosity and granularity of soils), the natural environment (hydrography, forest and vegetation), various networks (roads, railways, drainage) and human action (land use, implementation of development policies) and intrinsic flood triggering factors, we modelled the flood risk using Hierarchical Process Analysis (HPA) in the city of Thiès (Senegal).

After processing and analysing perception surveys of flood management stakeholders, we used HPA techniques to calculate coherence indices (CI) and coherence ratios (CR), which are respectively equal to 0.27 and 5% according to members of the ORSEC plan, and 0.21 and 4% according to people affected by flooding. These results show that the perception work approach is consistent and acceptable, and have made it possible to determine the flood risk index (FRI) of the stakeholders, who have many similarities. By implementing the FRI in ArcGis software, the flood risk map was generated automatically. This revealed a high risk of vulnerability of the main outlets occupied by human settlements. Our work enabled us to determine the overall vulnerability rate for the study area, which is equal to 10%, with a variant containing 4% high vulnerability affecting a total of 4,183 properties, compared with a medium vulnerability rate of 6% affecting a total of 8,847 properties.

Keywords: Flood; Hazard; Vulnerability; Factor; Risk; Consistency Index; Consistency Ratio; Hierarchical Process Analysis

1. Introduction

Floods are one of the most destructive disasters in the world, with considerable economic and social consequences and social damage that no other natural phenomenon in the world can match. [1] and [2]. They are also the main cause of natural disasters worldwide [3] and are the leading cause of natural disasters, claiming around 20,000 lives a year [4]. In 2009, according to the United Nations Organisation for the Coordination of Humanitarian Affairs, floods caused 200 deaths and affected 770,000 people in the West African sub-region [5] and [6]. The database of the Centre for Research on the Epidemiology of Disasters (CRED) at the University of Louvain shows that, between 2000 and 2020, natural disasters have not been mitigated or curbed [7]. In fact, the entire Sahel region has been affected by flooding on an unusual scale, from the Atlantic coast to Ethiopia and Somalia [8].

Flooding is one of the most serious threats facing Senegal; over the last decade, the phenomenon has become more frequent and more long-lasting [9]. Flooding affects virtually every region of Senegal [10]. According to the Department of Flood Forecasting and Management, in a group of 29 localities studied, exposure to the risk of flooding affected more than 2.4 million inhabitants, i.e. 13.5% of the national population, and almost 20% of the built-up areas studied were in floodprone zones [11] and [33]. The causes of flooding are partly linked to a lack of preparation, shortcomings in prevention, uncontrolled land use and the absence of a genuine early warning system. There have also been partial

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declassifications of classified forests (Thies and Pout), uncontrolled land use, particularly in flood-prone areas, and violent run-off and the return of exceptional rainfall often cause flooding in the town of Thies [33].

To combat flooding, decision-makers have adopted resolutions at Conferences of the Parties aimed at resolving this scourge once and for all. Scientific research has become involved in the fight against flooding by implementing hydrological models to provide definitive solutions to the harmful effects of flooding [33]. The State of Senegal has put in place several ORSEC plans (emergency organisation and management plan) and funding mechanisms to combat flooding. Despite all this, in October 2024, flooding resurfaced in the north of Senegal, affecting more than thirty-five thousand people and causing damage and loss of life. This prompts us to ask questions about the effectiveness of the implementation of flood control strategies and the sustainability of flood solutions. Aren't the series of strategies implemented to combat flooding pseudo-solutions?

To this end, we have advocated multicriteria analysis in this study, which provides decisionmakers with tools for solving complex decision-making problems where several criteria must be taken into account in the choice of options [12]; [13]; [14] and [33]. With this in mind, we opted for the hierarchical process analysis (HPA) method, which is a multi-criteria analytical approach to decision support developed by Saaty [15] and [16]. With this method, we are working on the technique of comparison by pair of factors in order to model the perceptions of stakeholders (members of the ORSEC Plan and people affected). More specifically, we intend to model flood risk using the hierarchical process analysis (HPA) initiated by [17].

2. Material and methods

2.1. Location of the study area

The study area is located 70 km from Dakar, the capital of Senegal, between parallels 14° 45' 00'' and 14° 51' 00'' north latitude and meridians 16°52' 00'' and 17°01' 00'' west longitude (Figure 1).

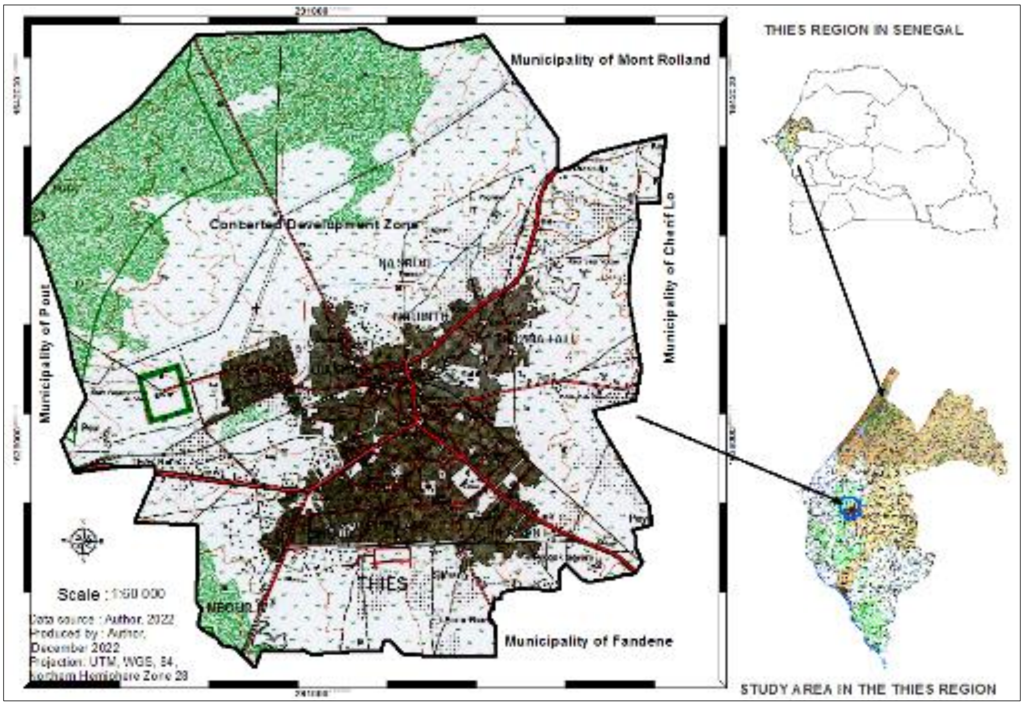

Figure 1 Location of the study area in the Thies region (data source: ANAT, 2020)

The study area covers 88.24 km^2, or 1.34% of the Thiès region. The study area comprises a large basin to the north with a surface area of 65.58 km^2 and a total length of the hydrographic network of 58.517 km, giving a drainage density of 0.89 km- 1, a medium basin to the south with a surface area of 15,71 km^2 with a total length of the hydrographic network of 11.645 km, i.e. a drainage density of 0.74 km-1 and a small basin to the east with a surface area of 690 km^2 and a total length of the hydrographic network of 23.35 km, i.e. a drainage density of 0.34 km-1 [33].

2.2. Choice of comparison factors

To carry out this work, we identified and selected two flood risk factors: active factors and passive factors. The passive and intrinsic factors we selected relate to the physical environment (slopes, permeability, porosity and granulometry of the soil), the natural environment (plant cover, forest and hydrography), the various networks (density of the hydrographic network, roads and railways, sewerage and rainwater drainage network), and human action (land use and implementation of development policies (household waste and buildings) [33]. The choice is justified by the physical configuration of the environment, its extent and the impact of human activity. The active factors are linked to rainfall in terms of intensity, frequency and extent. Our work shows that the Thies region is crossed by six isohyets divided into several classes.

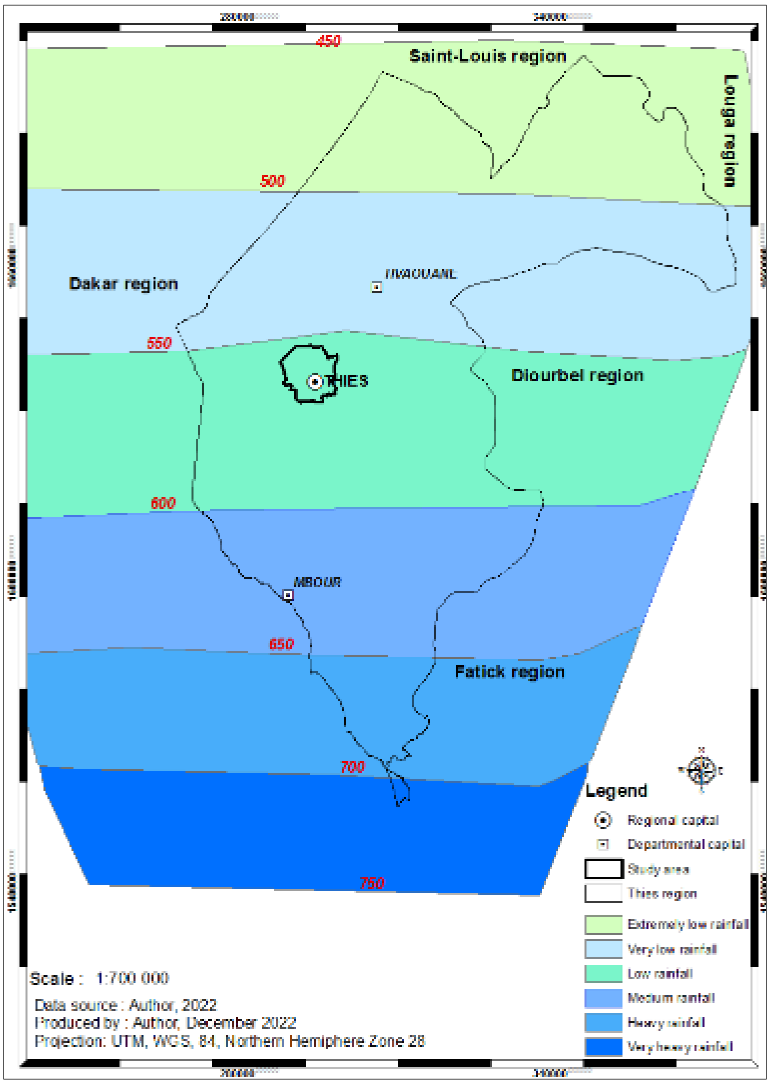

Figure 2 Spatial distribution of isohyets in the Thies region 'Data source: ANACIM, Database, 2018

The study area, which lies between isohyets of 550 mm and 600 mm rainfall, has no rivers or lakes [33]. The spatial homogeneity of rainfall, characterized by the existence of an isohyet, led us to omit it from the pairwise comparative analysis of flood risk, as well as runoff and flooding factors, even though they may play a fundamental role in other similar situations. We have therefore omitted rainfall (frequency, duration and intensity), flooding and runoff in the choice of flood risk factors and retained the intrinsic factors [33].

2.3. Materials

For this study, the target groups concerned by the problem of flooding in the study area, i.e. the members of the Organization and Rescue Plan (ORSEC) in charge of flood management and the people affected by flooding, were first identified [33]. This approach made it possible to collect data on the perception of flood factors by the target groups. To do this, we collected data on soil permeability using the Lefranc test. Darcy's law was used to calculate the soil permeability coefficient (k) according to the following relationship:

$$kSi = Q \qquad \text{............(1)}$$

Q: Flow velocity in m/s

i: Hydraulic gradient in m/m

S: Infiltration surface, corresponding to all surfaces in contact with water (in mm)^2

k: Permeability in m/s

To produce the soil permeability map, we classified the soil according to Table 1:

Table 1 Classification of the permeability coefficient

Coefficient of permeability K (m/s)	Interpretation
$1.692x\ 10^{-7} < k < 1.01x\ 10^{-6}$	Very watertight
$1.01x\ 10^{-6} < k < 8x\ 10^{-6}$	Low permeability
$8x\ 10^{-6} < k < 10x\ 10^{-6}$	Moderately permeable
$10x\ 10^{-6} < k < 2x\ 10^{-5}$	Permeable
$2x\ 10^{-5} < k < 5x\ 10^{-5}$	Very permeable

This classification was used to draw up the soil permeability map, which will be used as input data for mapping susceptibility to flood risk and for determining the risk susceptibility index.

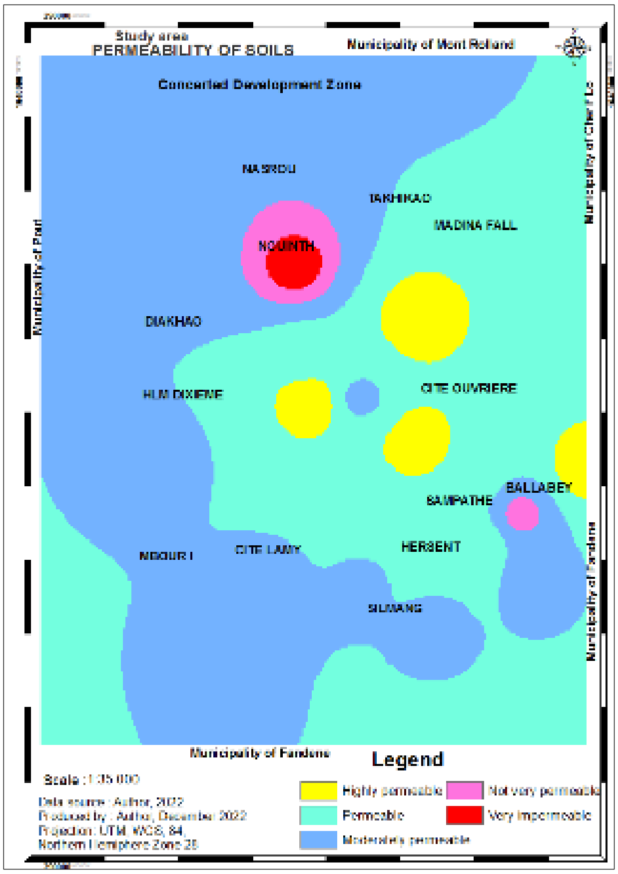

Figure 3 Permeability map

Figure 3 shows that soils with low permeability are located in runoff zones occupied by anarchic populations [33]. Figure 3 will be used as input data for the hierarchical fuzzy process analysis. We also collected "SRTM Plus" data (ASTER, 2013) to produce the digital terrain model.

Figure 4 shows that the study area lies in a basin at the top of which, further to the east, is a ridge with a surface area of 140 hectares and a perimeter of 6,976 meters.

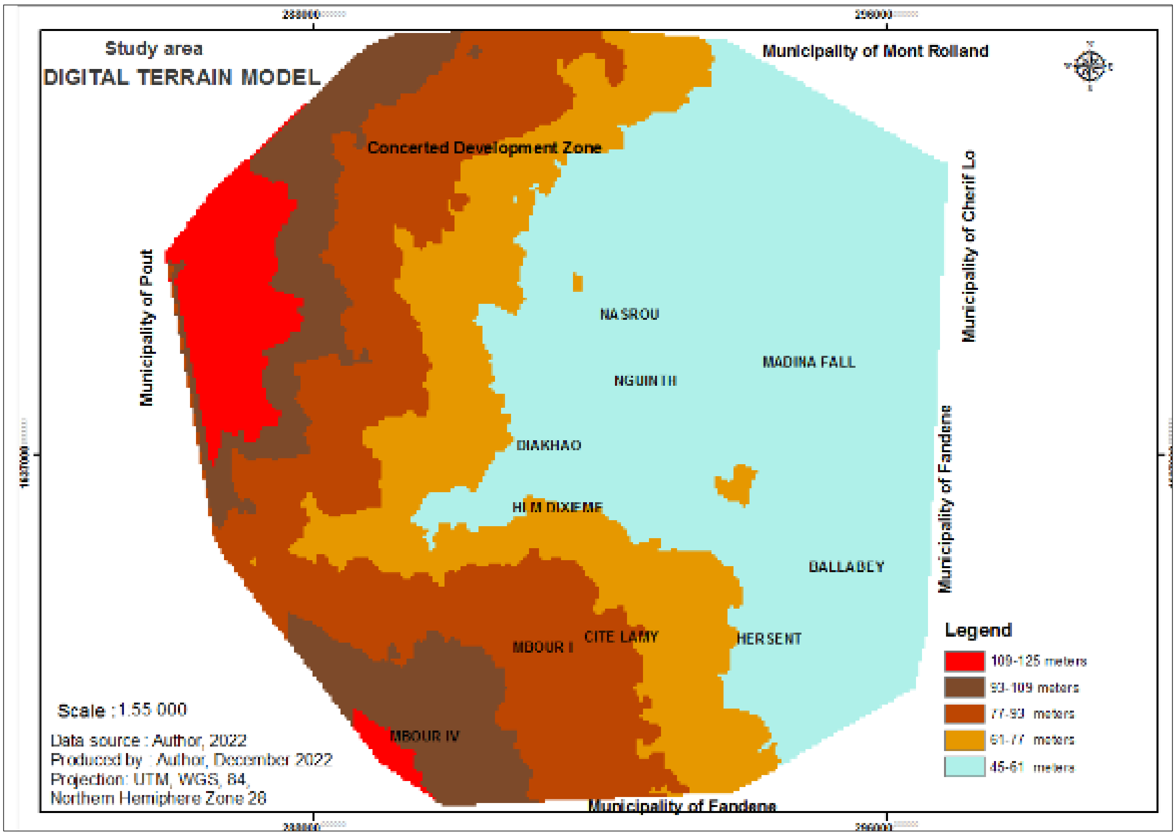

Figure 4 Digital terrain model

The ridge is 124 meters high. Below this ridge, between 46 and 89 meters above sea level, lie the administrative center, the primary, tertiary and quaternary sectors, as well as the fencing and security forces. Figure 4 provides an introduction to the hierarchical analysis of fuzzy processes.

To determine the normalized difference vegetation index (NDVI), we used remote sensing techniques to calculate plant biomass, identify flooded areas and soil typology [33]. We also used Landsat 8 Oli images to determine NDVI. The Arc GIS Raster Calculator tool was used to apply the equation 2 formula for the normalized difference vegetation index (NDVI), which was used to produce the forest cover map.

$$NDVI = \frac{NIR-R}{NIR+R} \quad \text{............(2)}$$

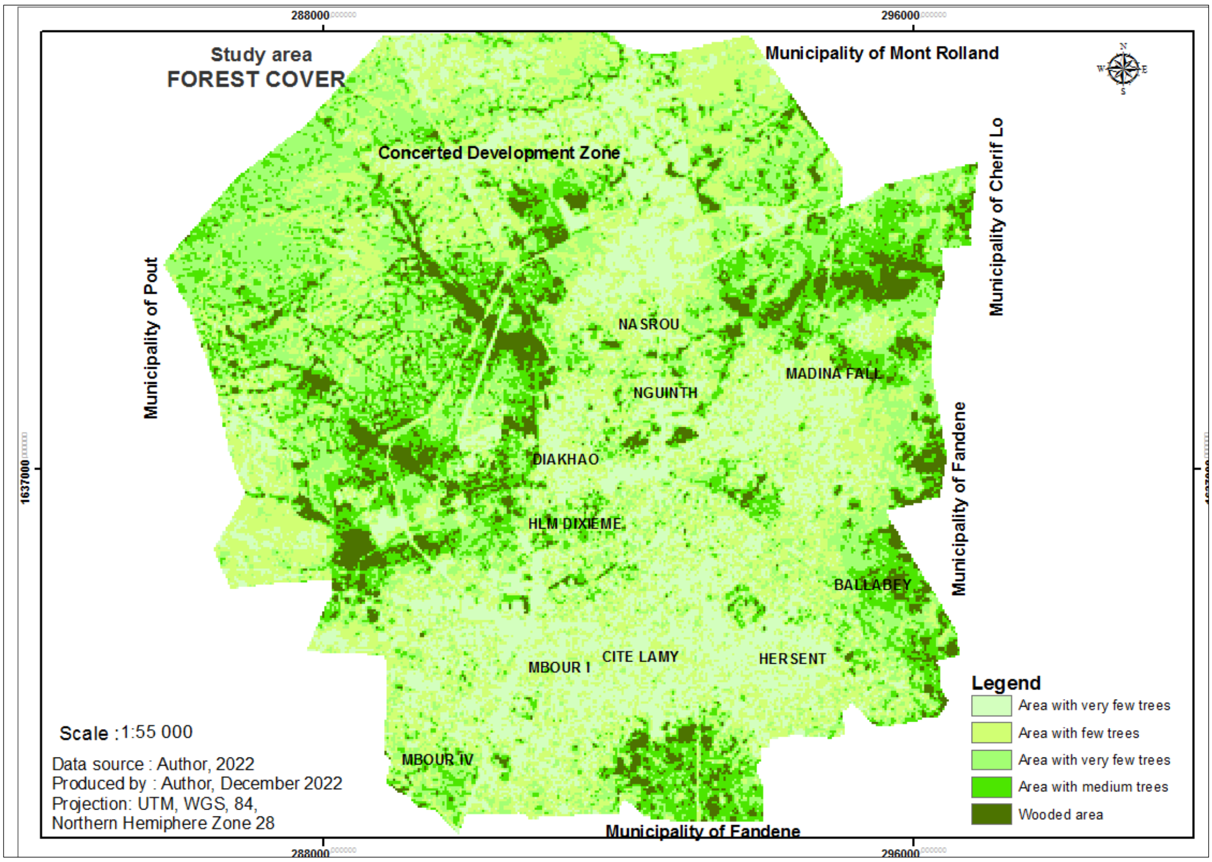

Figure 5 Forest cover in the study area

We also classified the vegetation cover data into five classes with an average amplitude of 7476 pixels. These classes are rated from 1 to 5 and are presented as follows:

- Treed vegetation zone (comprising 7476 pixels),
- Semi-wooded vegetation zone (comprising 16886 pixels),
- Medium tree vegetation zone (comprising 24549 pixels),
- Sparse vegetation zone (comprising 28973 pixels) and
- Very sparse vegetation zone (comprising 20155 pixels).

Figure 5 will serve as an input to the hierarchical fuzzy process analysis. We also used a handheld GPS receiver to study fuse discharges in order to locate them.

We have classified household waste landfills (Figure 6) according to their surface area into small, medium and large landfills, rated 1, 3 and 5 respectively. These ratings will be used in the modeling.

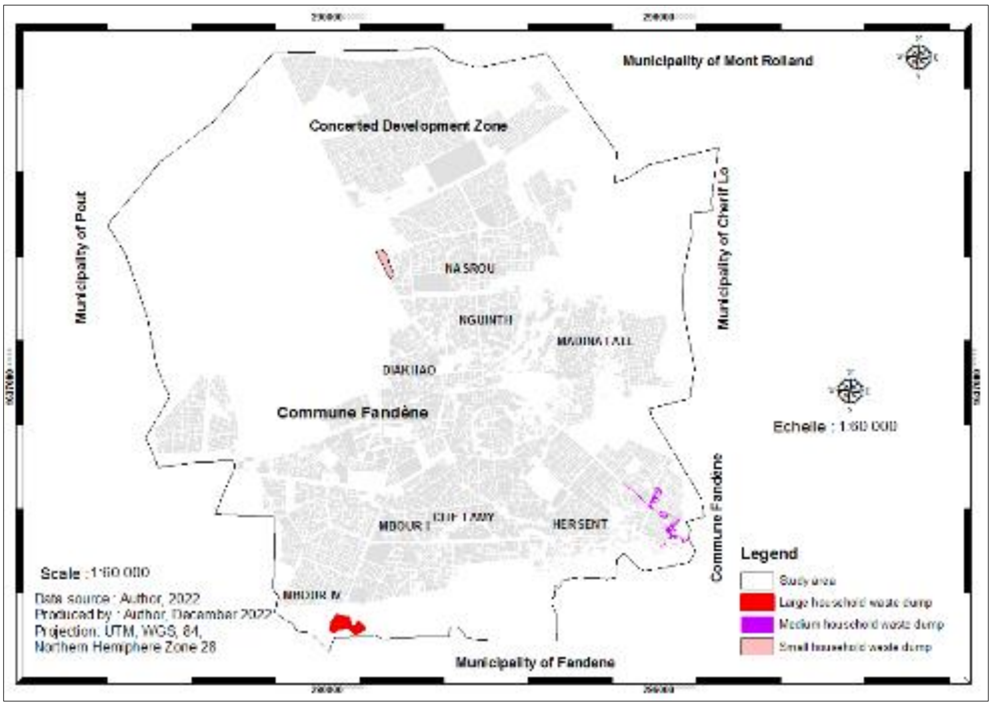

Figure 6 Map of household waste dumps

We have classified household waste landfills (Figure 6) according to their surface area into small, medium and large landfills, rated 1, 3 and 5 respectively. These ratings will be used in the modeling.

Figure 7 shows the diverse network made up of a set of linear features relating to hydrography, railroads, roads and stormwater channels. Data on railroads and roads were collected from the land register. Data on storm drainage channels was collected using GPS.

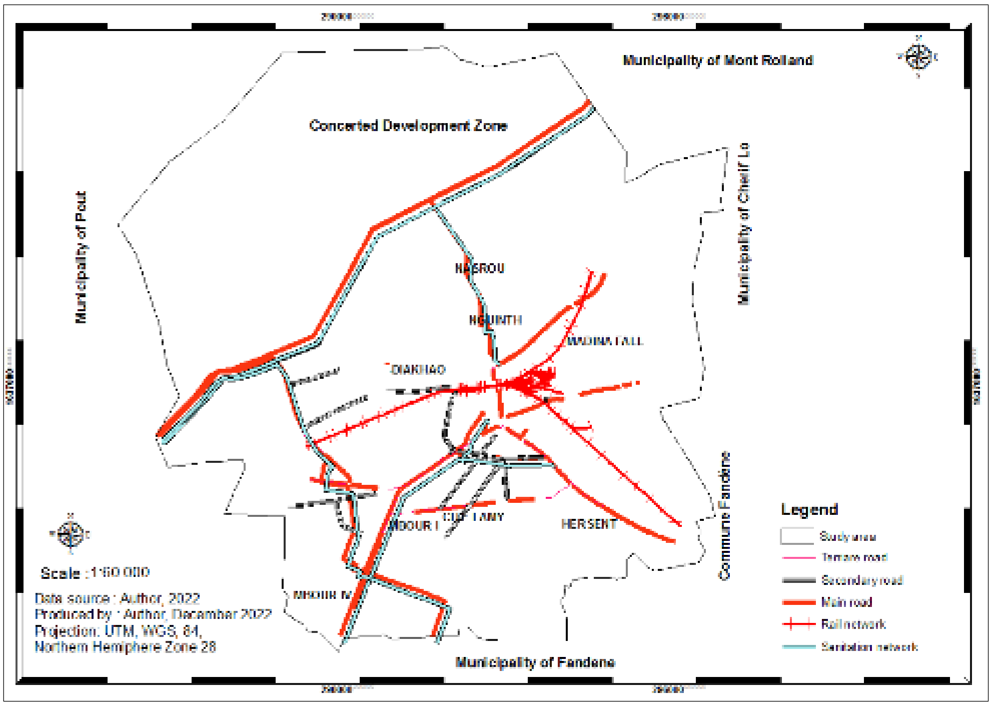

Figure 7 Map of networks

Data on the hydrographic network were obtained by remote sensing. After correcting and processing the Aster imagery, we produced maps of the hydrographic network. The steps involved in determining the hydrographic network. By superimposing the parcel data on the soil permeability data layer, we were able to obtain a composite layer covering the potentially flood-prone parts of the study area.

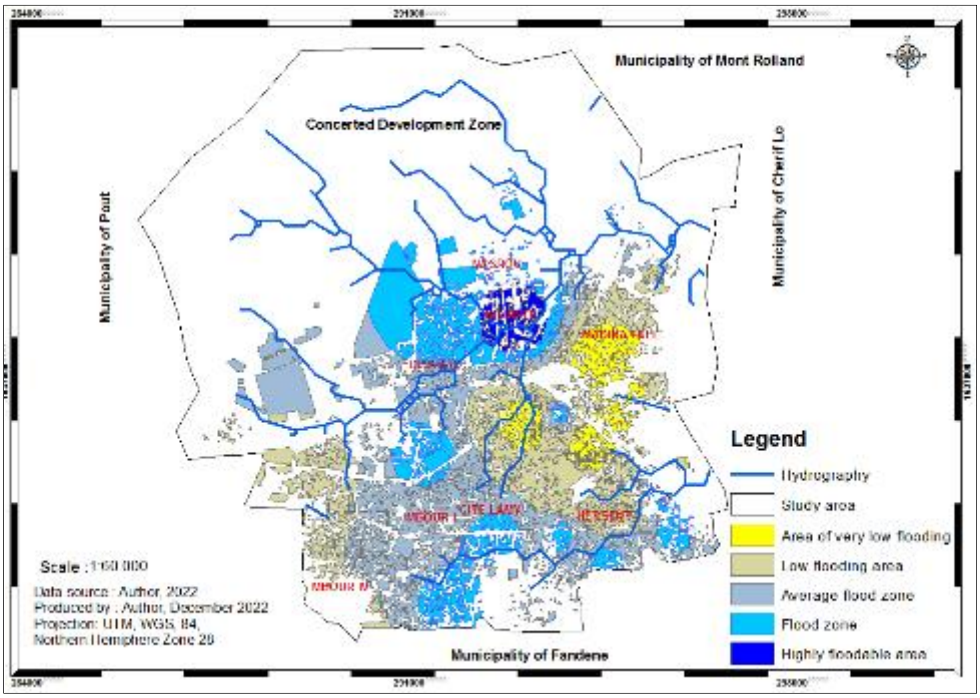

Figure 8 Flood zone map

Potentially flood-prone areas (Figure 8) have been classified into five categories, as follows :

- The very low flooding zone, covering an area of 195 ha
- The low-flood zone, covering an area of 632 ha
- The medium flood zone, covering an area of 888 ha;
- The flood-prone zone covers an area of 566 ha;
- The highly floodable zone covering an area of 72 ha

These data layers are rasterized, classified, downgraded and weighted from 1 to 5 according to their influence on flood frequency.

We used three types of software for processing, interpreting and analyzing the data: Sphinx Primo version 4.5 for editing the questionnaires, IBM SPSS for processing and analyzing the perception data from the pairwise comparison of factors, and Arc Gis version 10.5 for drawing up the flood risk map and determining the physical damage [33].

To collect data on the perception of the factors, we administered a questionnaire to fifty (50) members of the ORSEC plan (78% from the civil service, 8% from the private sector, 6% from local authorities, 6% from civil society and 2% from the Regional Development Agency (RDA) and to people affected by the floods [33]. We also administered 288 questionnaires to the people to be surveyed, applying a sampling rate of 11%. To do this, we made a selection by overlaying the data from the two soil types with the 6404 plots affected by the runoff effect. Using the intersection tool, we found 2,580 plots, or 40% of the total number, to which we applied a sampling rate of 11%, giving us a representative sample of 288 people to survey. This sample was made up of notables (55%), members of women's groups (11%), religious guides (11%), neighbourhood delegates (7%), members of community organizations (6%), grassroots community organizations (6%) and other categories (4%) [33].

2.4. Methods

AHP is one of the most widely used methods in spatial multicriteria decision analysis [15]. The AHP method is used in many fields, including multicriteria decision-making [15]; [14] and [19]. It is based on complex calculations using matrix algebra [20] and [21]. The AHP makes it possible to take account of possible uncertainties, social differences and the judgements of decisionmakers in certain respects when there is an explicit lack of technical or historical data [22]. The AHP method reduces the complexity of a decision problem to a sequence of pairwise comparisons, which are synthesised into a ratio matrix that provides a clear rationale for ordering the more and less desirable decision alternatives [23]. The implementation of AHP requires a number of steps [24]; [25] and [20] systematised into twelve techniques (Figure 9).

In technique 1, we identify and analyze the flooding problem in the study area, setting out the context, the problem and the approach to the work (definition of the material). ***Technique 2*** consists in defining the flooding problem, indicating the objectives to be achieved. ***In technique 3,*** we break down the problem into decision elements in the form of detailed criteria and scenarios for flood control. In effect, this decomposition of the flooding problem into adapted response scenarios will make it possible to manage this phenomenon intrinsically. This brings us back to ***technique 4***, which involves designing the conceptual data model (figure 9).

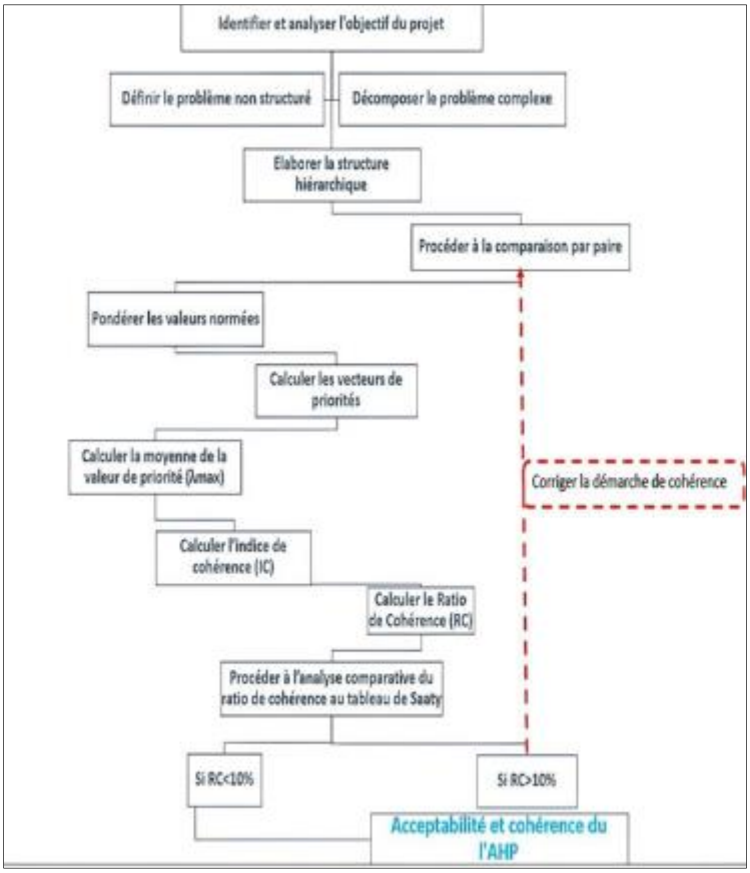

Figure 9 AHP installation techniques

Technique 5 provides an understanding of the hierarchical structure of the flooding problem in the study area. It is summarised in Figure 10, which shows the link between the main objective (flood risk modelling), the factors (active and passive), the criteria relating to uncontrolled urbanisation, the environment, the socio-economic situation, and the physical and climatic aspects, including rainfall. These are each broken down into sub-criteria (issues). These relate to buildings, the various networks (rainwater and wastewater drainage, as well as roads, bridges and the drinking water network), forests and plant cover, household waste, plots of land, property and activities, slopes (relief), soil type, soil permeability and isohyets. Each factor is then broken down to the level of sub-criteria or issues, which, with the application of the weighting system, makes it possible to propose a variety of scenarios. This technique has been used by [20] which states that the problem must first be decomposed into a hierarchical system, in which combinations are established at each level of the hierarchy. However, we have only worked on the passive factors intrinsic to the occurrence of floods in the study area.

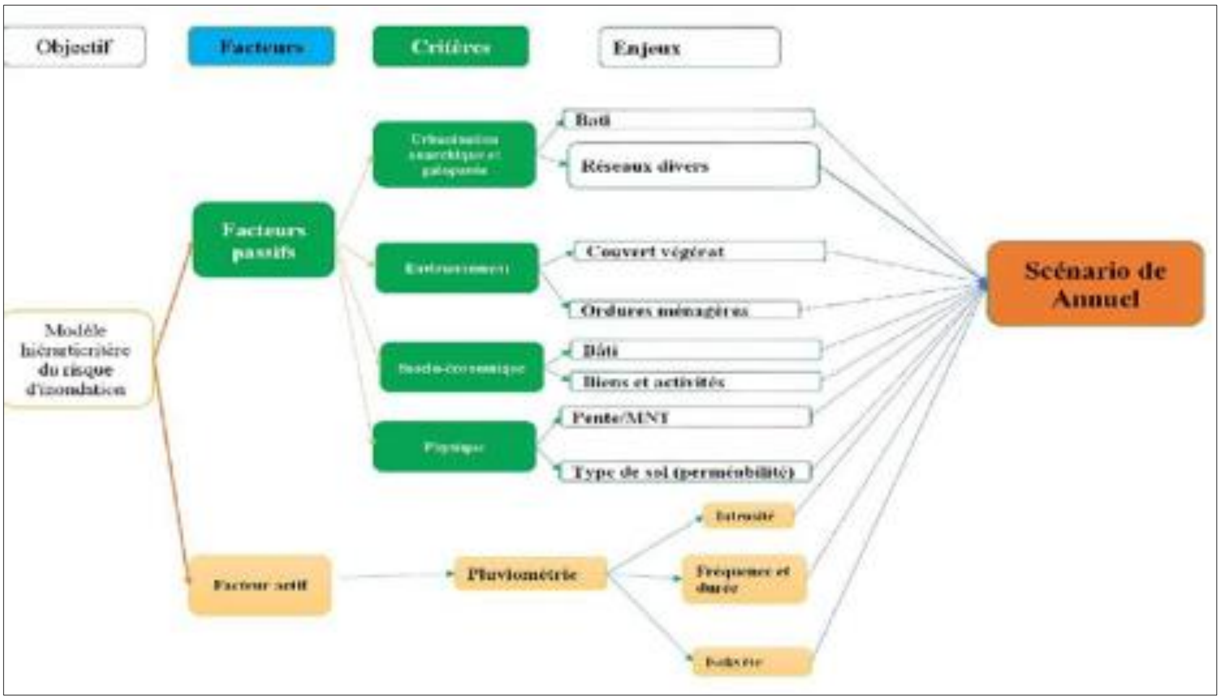

Figure 10 Conceptual diagram of flood risk according to the AHP model

After creating the conceptual data model (CDM) of the AHP, we will implement ***technique 6,*** which consists of a matrix comparison by pair of factors (CMPF) on the linguistic variables, which are qualitative data derived from the lessons learned by flood management stakeholders (Table 2).

Table 2 Pairwise qualitative comparison matrix

	P	**TSP**	**CV**	**RD**	**OM**	B
P	P*P =1	PTS*P	P*CV	P*RD	P*OM	P*B
TSP	TSP*P	TSP*TSP=1	TSP*CV	TSP*RD	TSP*OM	TSP*B
CV	CV*P	CV*TSP	CV*CV=1	CV*RD	CV*OM	CV*B
RD	RD*P	RD*TSP	RD*CV	RD*RD=1	RD*OM	RD*B
OM	OM*P	OM*TSP	OM*CV	OM*RD	OM*OM=1	OM*B
B	B*P	B*TSP	B*CV	B*RD	B*OM	B*B=1

(P: Slope; TSP: Soil type (permeability); CV: Plant cover; RD: Miscellaneous networks; OM: Household waste; B: Buildings)

The linguistic variables are converted into quantitative variables. This conversion uses the factor definition scale presented in Table 3. Each occurrence of a factor (Fij) in Table 2 is interpreted in rows and columns. A square matrix is then formed (known as a reciprocal matrix) of dimension e equal to the number of factors used, and each element of the matrix represents the relative contribution of one factor to another. [26].

Factor Pairwise Matrix Comparison (FPMC) is a numerical representation of the relationship between two factors (pairwise comparison) that share a common parent and allows the relative importance of one factor to be assessed in relation to another indicated. [20]. The values of these matrices are obtained by transforming the judgements into numerical values according to Saaty's scale while respecting the principle of reciprocity [22].

Table 3 Interpretation of factors - Scale proposed by [27]

Language variable (A /Band B)	Quantitative variable	Comments/interpretations
Equal importance	1	The two factors A and B are of equal importance
Medium importance	3	Factor A is moderately more important than factor B.
Medium reverse	1/3	Factor B is moderately more important than factor A
High importance	5	Factor A is much more important than factor B
Inverse high importance	1/5	Factor B is much more important than factor A
Very important	7	Factor A is much more important than factor B
Inverse very high importance	1/7	Factor B is much more important than factor A
Intermediate importance	2,4 and 6	Values associated with intermediate judgements

Qualitative data (table 2) relating to passive factors intrinsic to the risk of flooding, such as relief, soil type (permeability), vegetation cover, the various networks (roads, railways, waterways, drainage channels), household waste and buildings (tables 4 and 5) in the study area are converted into quantitative data (tables 6 and 7).

Table 4 Pair-wise comparison matrix of members' perceptions of the ORSEC plan for 2022

Factors	**P**	**TSP**	**CV**	**RD**	**OM**	**B**
P	1.00	4.32	4.24	4.92	4.60	5.32
TSP	0.23	1.00	3.92	4.32	4.80	5,08
CV	0.24	0.26	1.00	4.00	4.68	5.08
RD	0.20	0.23	0.25	1.00	4.84	5.24
OM	0.22	0.21	0.21	0.21	1.00	5.52
B	0.19	0.20	0.20	0.19	0.18	1.00
SOMME	2.08	6.21	9.82	14.64	20.10	27.24

(P: Slope; TSP: Soil type (permeability); CV: Plant cover; RD: Miscellaneous networks; OM: Household waste; B: Buildings)

Table 5 Pair-wise comparison matrix of the perception of people affected by flooding for the year 2022

Factors	**P**	**TSP**	**CV**	**RD**	**OM**	B
P	1.00	4.77	3.82	5.45	4.96	5.02
TSP	0.21	1.00	3.48	4.81	4.69	4.72
CV	0.26	0.29	1.00	4.38	4.37	4.52
RD	0.18	0.21	0.23	1.00	4.95	4.85
OM	0.20	0.21	0.23	0.20	1.00	5.05
B	0.20	0.21	0.22	0.21	0.20	1.00
SOMME	2.06	6.69	8.98	16.05	20.17	25.16

(P: Slope; TSP: Soil type (permeability); CV: Plant cover; RD: Miscellaneous networks; OM: Household waste; B: Buildings)

In ***technique 7***, we normalize the pairwise comparison matrix using the following relations

$$a = \frac{aa}{\Sigma(aa+ab+ac+ad+ae+ef)} \quad \text{..........} \ (3)$$

aa is the occurrence;

a standard occurrence;

The denominator corresponds to the sum of occurrences

We also calculate the weighting criterion for a factor (CP_{factor}) using the following equation:

$$CP_{facteur} = \frac{\Sigma P_{facteur}}{n} \text{............ (4)}$$

P_{factor} : is the value of the pairwise comparison and n is the number of factors

Once the weighting criterion has been calculated, the occurrences are weighted according to the following relationship:

CP_{factor} is the weighting criterion for the factor;

P_{factor} is the occurrence of the factor

In technique 7, we calculate the priority vectors by dividing the sum of the weighted values by the weighting criteria.

The priority vector (VP) is calculated from the following relationship:

$$\text{Weighted value} = CP_{factor} \times P_{factor} \quad \text{......... (5)}$$

Technique 8 involves determining the priority vectors based on the perceptions of flood management stakeholders in the study area.

$$VP = \frac{\text{Sum of weighted values}}{CP\ factor} \quad \text{............. (6)}$$

Table 6 Support for the calculation to validate the consistency of the perception of ORSEC plan members for the year 2022

Weighting criteria	**0,40**	**0,23**	**0,16**	**0,11**	**0,07**	**0,03**	**Sum of weighted values (SVP)**	**CPf Factor**	**Priority vector (VP)**
Factors	**P**	**TSP**	**CV**	**RD**	**OM**	B			
P	0.39	1.00	0.67	0.54	0.33	0.18	3.12	0.40	7.89
TSP	0.09	o.23	0.62	0.48	0.34	0.17	1.93	0.23	8.33
CV	0.09	0.06	0.16	0.44	0.33	0.17	1.25	0.16	7.93
RD	0.08	0.05	0.04	0.11	0.34	0.18	0.80	0.11	7.28
OM	0.09	0.05	0.03	0.02	0.07	0.18	0.45	0.07	6.29
B	0.07	0.05	0.03	0.02	0.01	0.03	0.22	0.03	6.52
Total									44.24

Table 7 Support for the calculation to validate the consistency of the perception of people affected by flooding for the year 2022

Weighting criteria	**0,40**	**0,23**	**0,16**	**0,11**	**0,07**	**0,03**	**Sum of weighted values (SVP)**	**CPf Factor**	**Priority vector (VP)**
Factors	**P**	**TSP**	**CV**	**RD**	**OM**	B			
P	0.40	1.08	0.61	0.59	0.35	0.18	3.20	0.40	8
TSP	0.08	0.23	0.55	0.52	0.33	0.17	1.88	0.23	8
CV	0.11	0.07	0.16	0.47	0.30	0.16	1.27	0.16	8
RD	0.07	0.05	0.04	0.11	0.35	0.17	0.78	0.11	7

OM	0.08	0.05	0.04	0.02	0.07	0.18	0.44	0.07	6
B	0.08	0.05	0.04	0.02	0.01	0.04	0.24	0.04	7
Total								1	44

Technique 9 relates to the method of calculating the average of the priority value (λmax) by means of the following relationship:

$$\lambda max = \sum_1^n \frac{Vecteurs\ de\ priorité}{critères\ (n)} = 7{,}37\ avec\ n = 6 \quad \ldots\ldots\ldots\ldots\ldots (7)$$

Technique 10 involves determining the coherence index, as proposed by [17]. This index is used to check the relevance and consistency of expert judgements [21]; [28] and [29]. We calculated the coherence index using the following equation:

$$IC = \frac{\lambda max - n}{n-1} \quad \ldots\ldots\ldots(8)$$

The IC of the members of the ORSEC Plan and the people affected by floods is 0.27.

In technique 11, we determine the Consistency Ratio (CR) using the following

$$RC = \frac{IC}{n} = 5\% \quad \ldots\ldots\ (9)$$

The coherence ratio is the ratio between the coherence index (CI) and the sum of the factors [30] and [21]. The consistency ratio (CR) is used to indicate the probability that the judgments in the matrix were generated randomly [31]. Its comparison with Saaty's random table 8 (TAS) makes it possible to assess the degree of acceptability of the matrix [21].

In technique 12, we carry out a comparative analysis of the consistency ratio with the Saaty table. The coherence ratio must be compared with the values given in Table 8, which deals with the number of factors and the value of the random indices (IA) developed by [17]. It is used to assess the consistency of the approach.

Table 8 Random index (RI) values [23].

N	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
IA	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51

According to the authors [28], [13], [21], [20] and [32] if the consistency ratio RC is greater than or equal to 10%, this shows that the approach is acceptable. Consequently, we found a CI of 0.27 and an OR of 5%. We assume that the data collected from the players followed an acceptable and consistent pairwise comparison approach.

3. Results and discussion

3.1. Agglomerative hierarchical grouping of stakeholder perceptions

Perception survey data from fifty (50) members of the ORSEC Plan for 2022 show that, whatever their perception of the slope and soil types, the slope and plant cover, the slope and various networks, the slope and household waste and the slope and buildings, the sample is made up of three homogeneous blocks (Figure 10). A homogeneous block is defined as a group whose individuals share the same overall perception.

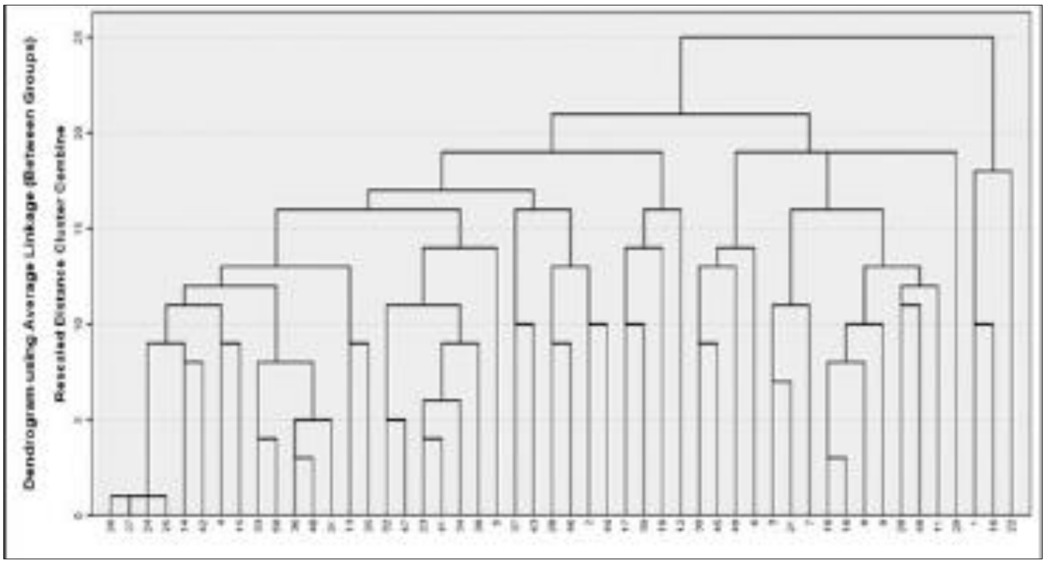

Figure 11 Agglomerative hierarchical grouping of ORSEC Plan members

However, the first agglomerative group is dominant, with 64% of similar perceptions. The second block has only 32% similar perceptions and the third contains 4% perceptions.

On the other hand, analysis of the perception survey data from two hundred and eighty-seven (287) people affected by the floods shows that, whatever the perception of the slope and soil types, the slope and plant cover, the slope and various networks, the slope and household waste and the slope and buildings, the sample is made up of three homogeneous blocks (Figure 12).

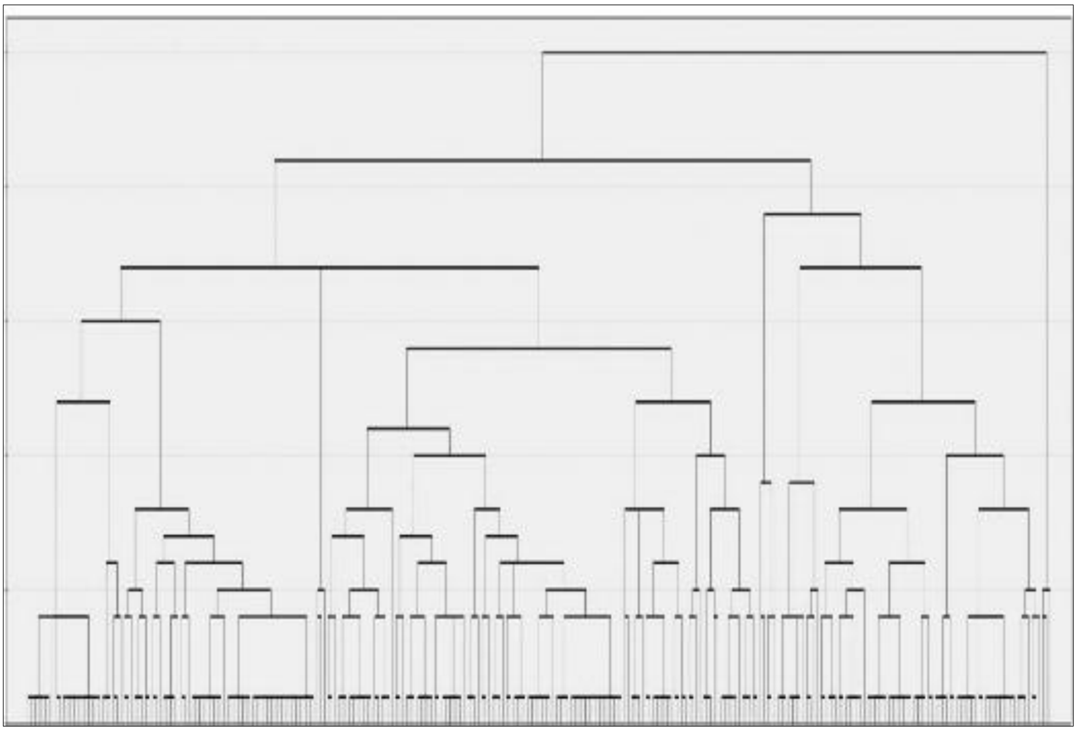

Figure 12 Agglomerative hierarchical grouping of the perceptions of people affected by flooding

Figure 12 shows that the first agglomerative group is dominant, as the data analysis reveals that it contains 71% of similar perceptions. The second block contains only 28% of similar perceptions and the third contains 1%.

Finally, we note that the vast majority of members of the ORSEC Plan and people affected by flooding have a similar perception of the influence of physical and man-made factors on the occurrence of flood risk in the study area. This similarity of perception between two different categories of stakeholder from the point of view of scientific knowledge and research shows that people affected by floods are just as capable as managers of preparing, documenting and implementing effective strategies to combat natural disasters such as floods. Consequently, the involvement and participation of all stakeholders in the fight against floods is the solution to this phenomenon.

3.2. Calculating flood risk indices

We consider that the Flood Risk Index (FRI) is equal to the Global Factor Vulnerability Index (GVI) because the active factors are omitted in the procedure. The GFVI is equal to the sum of the weighting criteria and follows the following relationship:

$$\text{GFVI} = \Sigma CP_{factor} \quad \ldots\ldots\ldots\ldots\ldots (10)$$

$CP_{facteur}$ is the factor weighting criterion

We determine the FRI, which is equal to the product of the rainfall hazard and the overall factor vulnerability index (GFVI). To do this, we apply equation 12 below:

$$\text{FRI} = \text{Aléapluviométrie} * \text{GFVI} \quad \ldots\ldots\ldots.. (11)$$

The rainfall hazard is uniform throughout the study area. The spatial uniformity of the rainfall hazard means that its value is a constant and uniformly influences the IRI over the entire study area.

Assuming Aléa pluviométrie equals 1, the FRI is therefore equal to the GFVI.

$$\text{FRI} = \text{GFVI} \quad \ldots\ldots\ldots. (12)$$

As a reminder, the average of the ƛmax priority vectors is 7.37. The consistency index IC is 0.27 and the consistency ratio RC is 5% according to the perception of ORSEC plan members. The weighting criteria are therefore acceptable. This leads us to equation 14, which calculates the flood hazard according to this model.

$$\mathbf{FRIorsec}_{\mathbf{2022}} = 0.40P + 0.23TS + 0.16CV + 0.11RD + 0.07OM + 0.03B \quad \ldots.(13)$$

With regard to the perception of people affected by flooding, the mean of the priority vectors ($ƛmax$) is equal to 7.06, the CI is equal to 0.21 and the or is equal to 4%. This leads to the conclusion that the perception is coherent and the approach is acceptable.

$$\mathbf{FRIpers}_{\mathbf{2022}} = 0.40P + 0.23TS + 0.16CV + 0.11RD + 0.07OM + 0.03B \quad \ldots\ldots\ldots..(14)$$

We note that **the FRIorsec $_{2022}$ is equal to the FRIpers $_{2022}$** and that the contribution of physical factors predominates over man-made factors. This could reflect a similarity in the perceptions of the various stakeholders, as evidenced by the same flood hazard map.

3.3. Flood hazard mapping

Equations 13 and 14 show that the AHP FRI indices derived from the perceptions of ORSEC plan members and people affected by flooding are equal. To this end, we produced the flood hazard map using the Weighted Overlay tool (Figure 13).

Figure 13 shows exposure to flood risk in the study area according to the FRI index. The map shows the spatial distribution of vulnerability to the risk of flooding, showing the level of exposure of neighbour hoods and community facilities. In addition, the dissolve tool in the Arc Gis software was used to determine the degree of vulnerability of the study area.

Using ArcGIS software, we calculated the overall vulnerability rate for the study area, which is equal to 10%, compared with a high vulnerability rate of 4% and a medium vulnerability rate of 6%, with the contribution of physical factors (slopes, soil type and vegetation cover) dominating over man-made factors (various networks, household waste and buildings). This means that physical factors have a much greater influence on the occurrence of flooding than man-made factors.

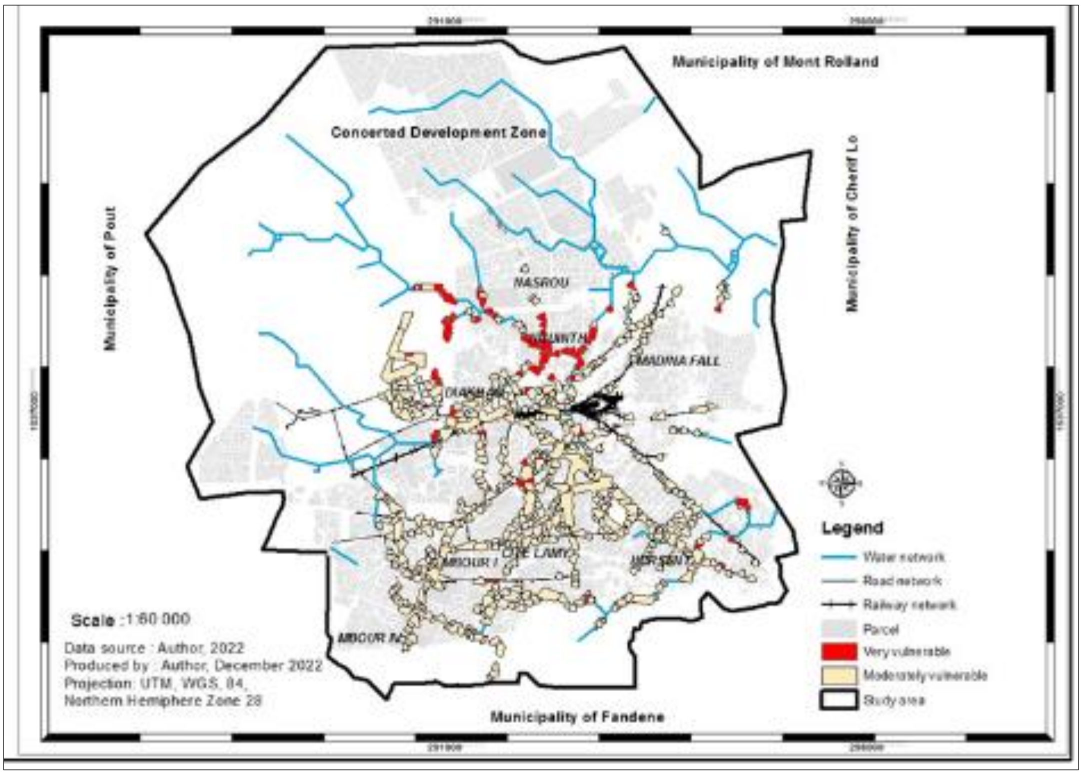

Figure 13 Flood hazard map based on the FRI index of members of the ORSEC 2022 plan and people affected according to the AHP model

The cartographic analysis also shows that, according to the AHP model of perception of the members of the ORSEC plan, out of a total of 4183 properties affected by high vulnerability to flooding, 68.66% represent inhabited houses compared with 10.23% bare plots, 6.91% houses under construction, 5.16% infrastructures, 3.28% bare fenced plots and the remainder other types of land occupation. We also note that according to the AHP model of the perception of people affected by flooding, out of a total of 8847 properties affected by average vulnerability, 75.46% represent inhabited houses compared with 6.80% bare plots, 6.77% infrastructure, 5.37% houses under construction, 2.31% bare fenced plots and the remainder other types of land occupation. This shows that no category of property would be spared the unpredictability of flooding.

In addition to determining the vulnerability rates of the study area and the number of properties affected by flooding, our work has integrated, unlike authors [1], [2], [3], [23] and [27] who have only worked on scientific techniques, linguistic variables expressed in the form of experience capital or endogenous knowledge of flood management stakeholders with matrix calculations and geomatics techniques to pose preventive flood management control strategies. This approach could constitute the particularity of our work which produced the map of the flood hazard in the study area. This map shows a spatial distribution of flooding, with the contribution of physical factors dominating over man-made factors.

4. Conclusion and outlook

As part of our work, we used pairwise comparison calculation techniques to determine consistency indices and consistency ratios to prove that the data collected from ORSEC plan members and people affected by flooding followed an acceptable and consistent comparison approach. To this end, the hierarchical process analysis produced the Flood Risk Index (FRI) from which we automatically generated the flood hazard map for the area with the help of ArcGis software. In addition, the results revealed that the contribution of anthropogenic factors is tending to take on worrying proportions as a result of the loss of plant biomass and anarchic occupation of space. It is therefore essential to reverse this trend in order to implement effective flood control strategies.

Consequently, we propose, as part of the prevention and strengthening of the resilience of areas exposed to the risk of flooding, the implementation of an early warning system for flood prevention and management that uses hierarchical process analysis to model the risk. Hierarchical Process Analysis can be used to predict the areas most vulnerable to flooding, to assess physical damage and injury, and to prepare for strengthening the resilience of highrisk areas. The system could be placed at the heart of a sub-regional and national observatory in which climatologists, forecasters and researchers will have to work in synergy to better manage natural disasters, particularly floods.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] M. T. M. O. O. M. KARROUCHI, Mapping of flood risk areas in the Tetouan region: the Oued Laou catchment area (North-West Morocco), International Journal of Innovation and Applied Studies, vol. 29, no. %1no 2, pp. 206-220, 2020.

[2] B. K. H. S. R. &. T. A. Merz, Valuation of Economic Damages Caused by Floods, Natural Hazards and Earth System Sciences, vol. 8, no. %11697-1724, p. 10, 2010.

[3] J. C. BERTONI, Urban flooding in Latin America:, vol. 305, no. %1123-141, p. 20, 2006.

[4] S. &. L. C. Niculescu, Sustainable floodplain management in the Danube Delta (Romania), Proceedings of the JSIRAUF, Hanoi, 2007.

[5] OCHA, Information Bulletin, October 2009, WB, 2009.

[6] L. Wallez, Flooding in West African cities: Diagnosis and elements for strengthening adaptation capacities in Greater Cotonou, University of Cotonou, 2010.

[7] EM-DAT, International database on natural disasters, 2020.

[8] T. P. G. &. V. T. Lebel, Flooding in Africa: a new hydroclimatic era, p. 6, 2020.

[9] H. G. M.-M. M. e. G. WANG, Preparing for Natural Hazards and Climate Change Risk Management in Dakar, Sénégal, The International Bank for Reconstruction, Dakar, 2009.

[10] S. F. S. D. M. K. M. &. K. N. R. Wade, 'Remote sensing of urban flood disasters: the case of the Dakar region (Senegal),' Journées dÁnimation Scientifique (JAS09) of the AUF Algiers, vol. , p. 7, 2009.

[11] M. Sene, Terms of reference for the formulation of a new ten-year flood management programme, DPGI, Ministry of Water and Sanitation, 2022.

[12] V. A. e. M. J. A. SALOMON, A compilation of comparisons on the analytic hierarchy processand other multiple criteria decision making methods: some cases developed in Brazil. 6th, 2-4 August 2001, Berne, Switzerland, p., at 6th International Symposium on the Analytic Hierarchy Process, Berne, 2001.

[13] J. M. M. B.-H. a. J. D. . m. e. f. d. p. l. e. l. g. T. J. M. B.-H. a. J. D. Tacnet, Analyse multicritères et fusion d'information pour l'expertise et la gestion intégrée des risques naturels en montagne, at Colloque LambdaMu, La Roche, 2010.

[14] M. C. BEKHTARI, Multi-criteria methods for analysing the suitability of agricultural land: the case of soft wheat in Languedoc-Rousillon analysed using the AHP method,, Languedoc-Rousillon: Université Paul Valéry de Monpelier, Master 2 Gestion Agricole et Territoires, 2016.

[15] J. e. a. Figueira, Multiple criteria decision support software. Multiple criteria decision analysis: state of the art surveys (2005): 989-1009, p. 37, 2005.

[16] S. M. V. &. S. R. Greco, The possible and the necessary for a multi-criteria group decision, at International Conference on Algorithmic Decision Theory , Heide, 2009.

[17] T. Saaty, The analytic hierarchy process (AHP) for decision making, Kobe, vol. 1, p. 69, 1980.

[18] M. S. R. P. J. T. B. Feizizadeh, An extended fuzzy multi-criteria evaluation on GIS for landslide susceptibility mapping, Department of Remote Sensing and GIS, University, 2014.

[19] A. e. a. Onana ntOuda, Contribution to flood hazard mapping in the Mfoundi catchment area in Yaoundé (Cameroun) using Multi-Criteria Analysis (MCA) based on the Hierarchical Analysis Process (HAP), vol. 44, n° %11327, p. 15, 2022.

[20] J.-B. Rakotoarivelo, (2018). Multi-Criteria Decision Support for risk management in the financial domain. École Toulouse Graduate School of Mathematics, Computer Science and Telecommunications: Computer Science and Artificial Intelligence, Toulouse: Université Paul Sabatier , 2019.

[21] A. e. a. Ramos, Application of the Hierarchical Multicriteria Analysis Method to the study of landslides in the coastal region of central Portugal: Figueira da Foz - Nazaré, Geo-Eco-Trop, vol. 1, no. %138, p. 12, 2014.

[22] K. K. H. e. G. S. Nigim, An effective multiple criteria approach to infrastructure reconstruction in devastated countries, Journal of Systems Science and Systems Engineering,, vol. 15, no. %12, pp. 232-246, 2006.

[23] B. e. Feizizadeh, Comparison of GIS-multicriteria decision analysis for landslides, sensitivity mapping for Lake Urmia basin, Iran, Center for Remote Sensing and GIS, University of Tabriz, p. 4, 2012.

[24] B. e. Besson, Douze méthodes d'analyse multicritère, Revue française d'automatique, d'informatique et de recherche opérationnelle. Recherche opérationnelle, vol. 3, 1971.

[25] M. e. A. Vahidnia, Hospital site selection using Fuzzy AHP and its derivatives, Journal of Environmental Management, no. %13048-3056, p. 90, 2009.

[26] R. CISSOKHO, Developpement d'un indice de vulnerabilite a l'erosion eolienne a partir d'images satellitales, dans le bassin arachidier du Senegal: Cas de la région de Thies. Ph. D. Thesis, Thiès: Universite de Montreal, 2012.

[27] Feizizadeh, An extended fuzzy multi-criteria evaluation on GIS for landslide susceptibility mapping. Department of Remote Sensing and GIS, University of Tehran, Iran,, Computers and Geoscience Edition, 2014.

[28] A. Guitouni, Engineering the choice of a multi-criteria aggregation procedure.Doctoral thesis defended at the Faculty of Graduate Studies, Laval University, Laval: Laval University, 2015.

[29] A. M. e. Z. A, Contribution of GIS to the study of groundwater quality using the hierarchical process analysis (HPA) method in the north-west region of Elouad (Algeria), Northwest region of Elouad (Algeria): Echahid Hamma Lakhdar El oued University, Faculty of Technology, 2019.

[30] D. H. ,. K. M. Belloula Moufida, Spatialization of water erosion using analytic hierarchy process (AHP) method in the high valley of the Medjerda, vol. 44, n° %119-25, 2020.

[31] B. Feizizadeh, Feizizadeh, B (2013). Integration of GIS-based fuzzy set theory in multi-criteria evaluation methods for landslide susceptibility mapping. International journal of geoinformatics, no. %181-98, 2013.

[32] B. C. F. H. D. D. C. e. G. G. SY, Reconstituting past flood events: the contribution of citizen science, Hydrology Earth System, no. %124, p. 14, 2019.

[33] Dieye, S., Ndiaye, M., Diouf, D. and Ba, M. (2024) Flood Risk Modelling Using the HFPA (Hierarchical Fuzzy Process Analysis) Method: Example of the City of Thies, Senegal. International Journal of Geosciences, 15, 1064-1086. doi: 10.4236/ijg.2024.1512056.