

Boulomytis, V. T .G.; Zuffo, A. C.; Imteaz, M. A.

Article

Detection of flood influence criteria in ungauged basins on a combined Delphi-AHP approach

Operations Research Perspectives

Provided in Cooperation with:

Elsevier

Suggested Citation: Boulomytis, V. T .G.; Zuffo, A. C.; Imteaz, M. A. (2019) : Detection of flood influence criteria in ungauged basins on a combined Delphi-AHP approach, Operations Research Perspectives, ISSN 2214-7160, Elsevier, Amsterdam, Vol. 6, pp. 1-12, <https://doi.org/10.1016/j.orp.2019.100116>

This Version is available at:

<https://hdl.handle.net/10419/246368>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by-nc-nd/4.0>



ELSEVIER

Contents lists available at ScienceDirect

Operations Research Perspectives

journal homepage: www.elsevier.com/locate/orp

Detection of flood influence criteria in ungauged basins on a combined Delphi-AHP approach

V.T.G. Boulomytis^{a,b,c,*}, A.C. Zuffo^b, M.A. Imteaz^a^a Department of Civil and Construction Engineering, Swinburne University of Technology, Australia^b School of Civil Engineering, Architecture and Urban Design, State University of Campinas - UNICAMP, Brazil^c Department of Civil Construction, Federal Institute of Science, Education and Technology of Sao Paulo - IFSP, Campus Caraguatatuba, Brazil

ARTICLE INFO

Keywords:

Decision analysis
 Decision-making process
 Multiple criteria analysis
 Criteria judgement scale
 Flood susceptibility evaluation

ABSTRACT

The prediction of areas susceptible to floods is essential for the protection of the population living in vulnerable conditions. It is only possible when the main contributing factors are pointed out. It is very challenging for hydrologists to run models when the input data are not representative. Alternative methods, such as the multicriteria decision analysis, represent a good solution for the simulation of future scenarios. However, the criteria selection affects the accuracy of the further modelling process. The purpose of the current study was to select and attribute scores to all the feasible criteria that contribute to flood susceptibility in the coastal plains of the Juqueriquere river basin, Brazil. First, the Delphi method was employed in the expert-based survey. Then, the root square judgement scale was adapted to an extended Analytic Hierarchy Process approach for the final allocation of priority values. Even though the initially ranked scores were within a limited range, the proposed methodology could adequately redistribute these scores in the final scale from 1 to 10. The consistency and sensitivity analyses revealed that the findings were coherent, providing the weight vector of the achievable criteria that affect the flood likelihood in the study area.

1. Introduction

Floods have always represented one of the most destructive natural hazards to the humankind. The occurrence of floods worldwide impacts human lives and jeopardise the economy of many regions [1,2]. In urban areas, the decrease of infiltration naturally occurs upon the increase of imperviousness. It subsequently generates a higher peak flow, in a shorter time, which flows to the outlet of the basin, increasing the load in the downstream areas. Besides, in the low-lying areas of coastal cities, floods tend to increase due to the tide variation effects [3].

For the prevention or attenuation of floods, it is essential to have full awareness about the hydrological behaviour of the basin, which depends on physical, climatic and anthropic aspects, such as the land use and land cover (LULC). Hydrological and hydraulic modelling are essential tools for the design of infrastructure but might be impaired when inappropriate techniques and variables are chosen [4,5].

Traditional methods of prediction are not always possible when data are unavailable, inconsistent or non-representative. Questions like “how does this or that variable control the hydrological phenomena in the area?” or “how sensible is the area to the magnitude of this or that variable?” are commonly raised by modellers. In case the watershed is

ungauged, and previous studies cannot efficiently reveal the significance of the model input parameters, it is challenging to choose an ideal approach to predict future scenarios.

The Multicriteria Decision Analysis (MCDA) has been effectively used by policymakers and urban planners for resolving conflicts regarding water resources [6–9]. Many studies have shown a significant improvement in flood management problems when MCDA is used [5,10–13]. One of the reasons is that the structured aggregation of elements, based on the expert's knowledge of the area or phenomena, cannot be comprehensively analysed by traditional hydrological methods. Besides, participatory processes of environmental governance are recognised to be useful for sustainable developments [14], addressing the global concerns that are not covered by local environmental tools [15].

The MCDA approach can be characterized by diverse mechanisms to achieve the contributing criteria and calculate the weight of each criterion. For instance, [16] studied the flood vulnerability of a region in China using a neuro-fuzzy inference system. Even though their methodology was coherent providing robust outcomes, it is important to notice that the study area which had been chosen for the proposed methodology was due to the data availability and the amount of 195

* Corresponding author at: Civil Construction, IFSP, Av Alagoas 216 Indaia, 11665160 Caraguatatuba, São Paulo, Brazil.

E-mail address: likitgb@yahoo.com (V.T.G. Boulomytis).

<https://doi.org/10.1016/j.orp.2019.100116>

Received 29 October 2018; Received in revised form 6 June 2019; Accepted 7 June 2019

Available online 08 June 2019

2214-7160/© 2019 Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license

(<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

monitored flood events.

However, there are not many alternatives for ungauged basins, which normally occur in underdeveloped countries. The amount of available data is not enough for calibrating and validating the criteria acquisition models. Moreover, input data for the estimation of criteria become more challenging and less trustworthy. Thus, the innovative purpose of the current research is to meet the demand of watersheds lacking monitoring data. Indeed, it gives the modeller the opportunity of determining the most significant criteria, responsible for controlling the hydrological processes of watersheds, even when data are limited. By means of a theoretical and systematic approach, each criterion is considered throughout the research, in a complex environment of coastal areas, with potential orographic rainfalls and low altimetry. In addition, the statistical and AHP treatment of the criteria weights also enhance their reliability towards the modelling process.

2. Material and methods

2.1. Multicriteria decision analysis

Among all the existing multicriteria evaluation techniques, there is a common purpose of providing the decision makers with aid to reach the ideal solution for a problem. Structured decision-making is essential for sustainable predictive models [6,7,9,17]. It enhances the effectiveness of the process and reduces the decision uncertainties [7,18]. In structured decision-making (DM) approaches, complex decisions can be divided into elements to simplify the construction and the evaluation of the process.

According to [19], consistent objectives (or criteria) must be essential, independent, controllable, operational, decomposable, non-redundant, complete, measurable, concise and understandable. A natural tendency of decision-makers is to define alternatives without completely explaining the objectives [7,8,17]. Conversely, decision situations cannot be controlled by this alternative-focused thinking approach, which identifies alternatives before articulating values. Alternatives are the means to achieve values. When the DM is based on value-focused thinking, the objectives are properly defined and associated to their quantitative functions [18].

The identification of the objectives is essential to achieve a decision in a smarter value-focused thinking approach [20]. The fundamental objectives (or ends) are related to the ultimate value of the DM (i.e. they are the broader objectives of the DM which have to be accomplished through decision making), while the means objectives are the methods to achieve the ends [19,21]. All the decisions strategically influence the objectives. Finally, process objectives concern how the decision has been made [17,20].

The structural identification of criteria is not a trivial task. It requires creativity and appropriate communication skills [18]. Making a list of objectives without profound concepts provides a weak set of alternatives [21]. A logical and structured discussion should be guided by sequential questions for each criterion. For instance, the use of “how” to ask about the means to be used to achieve the ends; and “why” to indicate the importance of the criterion and lead the ends back to the means, which, depending on the answer, may become an alternative. The “why” question has to be repeated until no further answers can be given, i.e. the respondent can only say that it is crucial for its own sake [21].

Cognitive maps are normally employed for the construction of objectives, improving the display of ideas and clarifying perceptions [22]. The main advantages of the cognitive mapping are the organised classification of the concepts and the simplified access and visualization of the previously discussed concepts [23].

In the current study, the Delphi method is applied to the expert-based survey. Then the Analytic Hierarchy Process (AHP) uses the root square judgement scale [24] adapted to an extended approach of [25]. The prior articulation of preferences among the experts, from the selection to the attribution of each criterion, was later ranked in a prioritisation mechanism of pairwise comparisons.

2.2. Delphi method

In a participatory process of knowledge and judgement, the selection and participation of motivated experts are crucial for the DM approach [26]. In the Delphi method, the participation of experts in the DM process is anonymous. The distribution of outcomes is represented statistically, and post-evaluation feedback is used to search for a consensual “ideal” solution (Fig. 1).

The method assumes that the structured use of knowledge, experience, and creativity of all the experts is better than the opinion of single individuals to achieve ideal solutions, especially when there is insufficient quantitative data to predict a scenario or when new factors may change future trends [27]. The negative effects caused by the interaction of groups, such as the respondent biases, can be avoided since the method works with written opinions [26]. Recent applications of the Delphi method are found in the field of sustainable development and policy planning, such as [26] and [28].

A disadvantage of the Delphi method is that the relative importance of the criteria might be reduced due to the proposed statistical treatment. By removing the judgement weights considered outliers (which occurs when these weights are out of the interquartile range), the distances among all the criteria weights tend to be narrowed between the values 7 and 9, while the initial scale ranges from 1 to 10 [25].

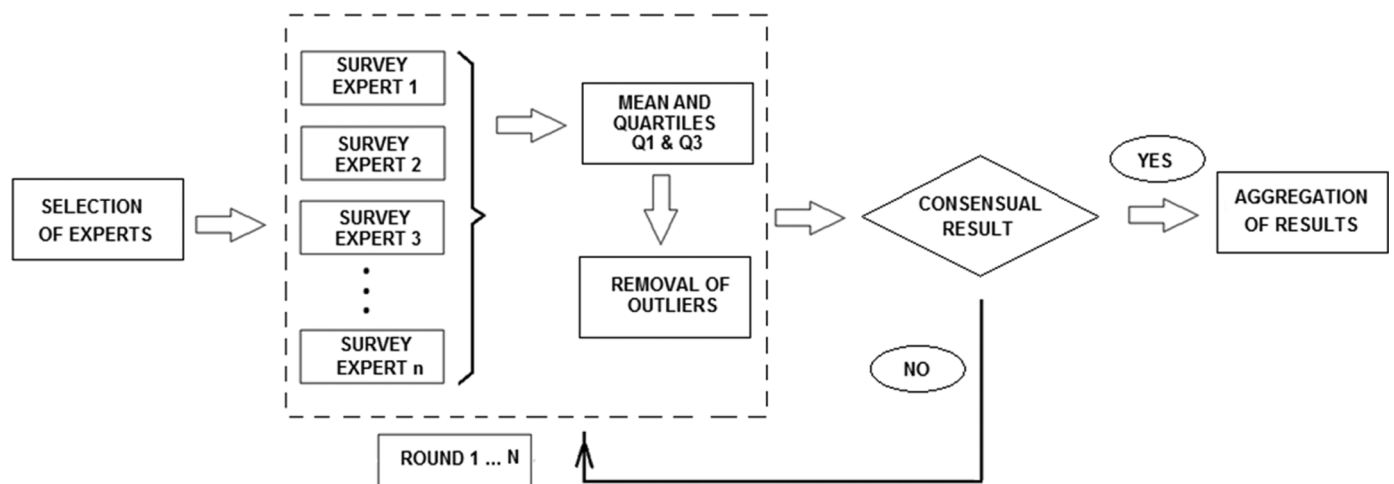


Fig. 1. The Delphi judgement procedure in a consensus-building process.

Table 1
Relative scores according to the level of importance of each criterion.
Source: Adapted from [33].

n	2	3	4	5	6	7	8	9	10
RI	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.51

However, before the use of the AHP, the weights and their importance level might be properly redefined again.

2.3. The analytical hierarchy process

This multilevel and hierarchical structural technique was developed by [29] and has been mainly used due to the simplification of complex and subjective problems [9,30,31]. The AHP evaluation is based on the pairwise comparison of the A matrix (n x n), given by:

$$A = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \dots & a_{nn} \end{bmatrix} = \begin{bmatrix} z_1/z_1 & \dots & z_1/z_n \\ \vdots & \ddots & \vdots \\ z_n/z_1 & \dots & z_n/z_n \end{bmatrix} \tag{1}$$

where n is the number of criteria, a_{ij} is the pairwise comparison (1 ≤ i, j ≤ n), which is the importance of criterion i according to criterion j, and z₁, z₂...z_n is the relative priority.

The A matrix is then normalized, and the matrix A' is achieved. For that, all the elements of the A matrix are divided by the sum of the respective element column.

$$A' = \begin{bmatrix} a_{11}' & \dots & a_{1n}' \\ \vdots & \ddots & \vdots \\ a_{n1}' & \dots & a_{nn}' \end{bmatrix} = \begin{bmatrix} a_{11}/\sum_{i=1}^n a_{i1} & \dots & a_{1n}/\sum_{i=1}^n a_{in} \\ \vdots & \ddots & \vdots \\ a_{n1}/\sum_{i=1}^n a_{i1} & \dots & a_{nn}/\sum_{i=1}^n a_{in} \end{bmatrix} \tag{2}$$

Accordingly, the sum of each row of the normalized judgement matrix A' leads to the definition of the vector matrix V.

$$V = \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix} = \begin{bmatrix} \sum_{j=1}^n a_{1j}' \\ \vdots \\ \sum_{j=1}^n a_{nj}' \end{bmatrix} \tag{3}$$

The vector matrix V is finally normalized and converted to the final weight vector matrix W.

$$W = \begin{bmatrix} v_1/\sum_{i=1}^n v_i \\ \vdots \\ v_n/\sum_{i=1}^n v_i \end{bmatrix} \tag{4}$$

2.3.1. Consistency analysis

One of the advantages of the AHP is the employment of consistency analysis to evaluate the outcomes. [29] initially proposed a methodology where the matrix highest eigenvalue (λ_{max}) is calculated using Eq. (5) for the definition of the consistency index (CI), as expressed by Eq. (6).

$$\lambda_{max} = \sum_{i=1}^n (Av)_i / (nv_i) \tag{5}$$

$$CI = (\lambda_{max} - n) / (n - 1) \tag{6}$$

Table 2
Classification of the judgement scales for consistency and priority-value allocation aspects.
Source: Adapted from [32].

Classification level	Consistency sensitivity	Variation of priority-value allocation
High	Root square, Logarithmic	Power, Geometric
Moderate	Linear, Power	Linear, Balanced
Low	Geometric, Inverse linear, Asymptotical and Balanced	Root square, Inverse linear, Asymptotical

With the advance of pairwise comparisons, it was also necessary to improve the evaluation of consistency errors [32]. Therefore, [33] recommended the measure of the consistency ratio (CR), given as:

$$CR = CI/RI \tag{7}$$

where RI is the random index (Table 1). The best solution would be for CI = 0. Thus, consistent values correspond to CR < 1.

2.3.2. Judgement scale selection

Depending on the judgement scale, the results may differ significantly [32]. The linear scale of [29] has been prevailing in the AHP studies since its proposal [26,32,34]. It varies from 1 to 9, and attributes priorities to the hierarchical structures according to their importance level. Level 1 represents equal importance, while level 9 indicates the dominant importance of a criterion compared to the others. Subsequently, other numerical scales have also been developed to indicate importance levels, based on specific mathematical concepts [34].

The selection of a judgement scale is not a trivial task, as the weight attributions of the decision-making process have their specificities. Some considerations for the proper selection of the judgement scale are:

- the limited range among the attributed scores [25];
- the evaluation of clustered-valued scores [32];
- the sensitivity analysis of the outcomes when integer values from 1 to 9 are used for disperse data [35];
- the variation of priority-value allocation [32];
- the scale sensitivity to consistent and inconsistent matrices [32].

Franek and Kresta [32] evaluated the consistency of the matrices and the variation of priority-value allocation of the judgement scales. For the consistent matrices, the most sensitive judgement scales were the root square and the logarithmic scales, and the criteria ranking was uniform for all the scales. The asymptotical and root square judgement scales provided the most uniform allocation of priority values. The final classification of judgement scales, according to their consistency sensitivity and priority-value allocation is summarized in Table 2.

2.3.3. The AHP extended approach of Zuffo

As stated before, a limited range of scores between 7 and 9 (in a scale from 1 to 10) mostly results from the employment of the Delphi method, which affects the relative importance given to the criteria [25]. The AHP extended approach of [25] enables an effective redefinition of the criteria scale originated by the Delphi method. Some of the adaptations to the traditional AHP approach are listed below:

- The criteria are initially ordered in descending order in a square matrix (n x n).
- The relative differences are calculated between the criterion i and the least dominant criteria, then between the criterion i + 1 and the least dominant criteria, successively.
- The relative differences are substituted with the numbers that define the Saaty's scale (i.e. varying from 1 to 9), forming an upper diagonal matrix with this scale.
- Finally, the weights are redefined using the traditional AHP approach, where the inferior matrix is filled in with the inverse of the row values in each column.

3. Description of the case study

3.1. Study area

The study area is located in Caraguatatuba municipality, along the northern coastline of the state of Sao Paulo, Brazil (Fig. 2a). As the plains are surrounded by the Serra do Mar Mountains, they are affected

by intense orographic rainfalls and high tides. Low elevation, shallow water tables and highly saturated soils are the main physical constraints. The average annual temperature is 25 °C, and the average annual precipitation (measured between 1977 and 2015) is 1652.8 mm. The weather is subtropical and rainy, especially in the summer. The downstream area of the plains is already urbanised, while the upstream area is rural, mostly covered by pastures and cultivated lands. Both

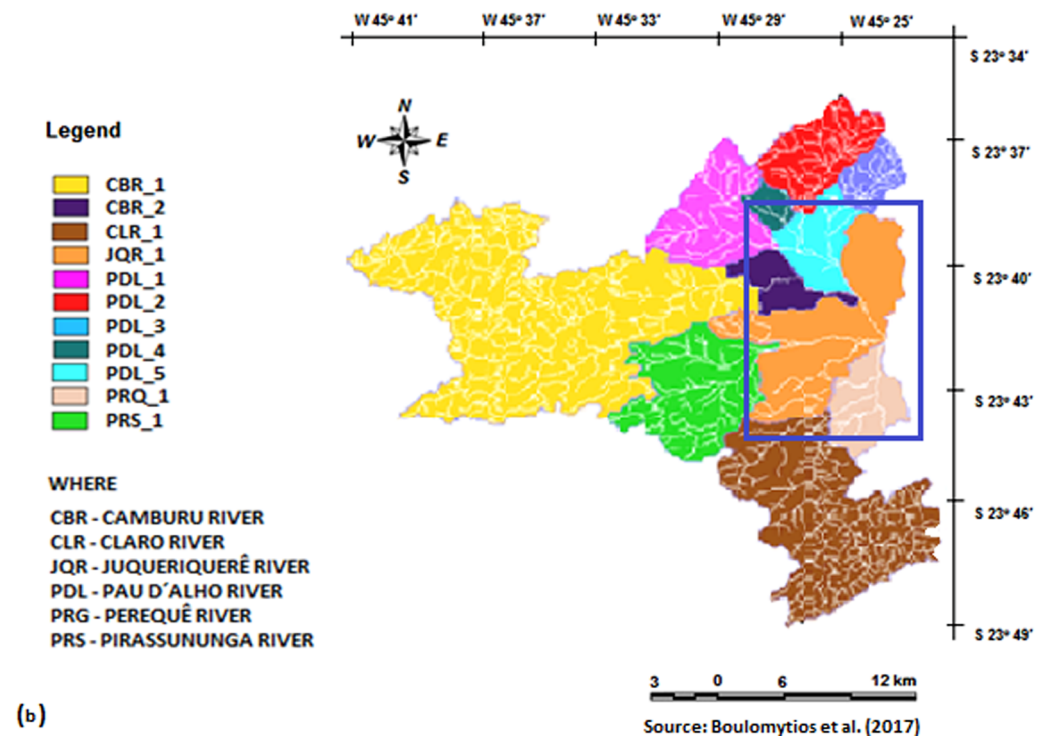
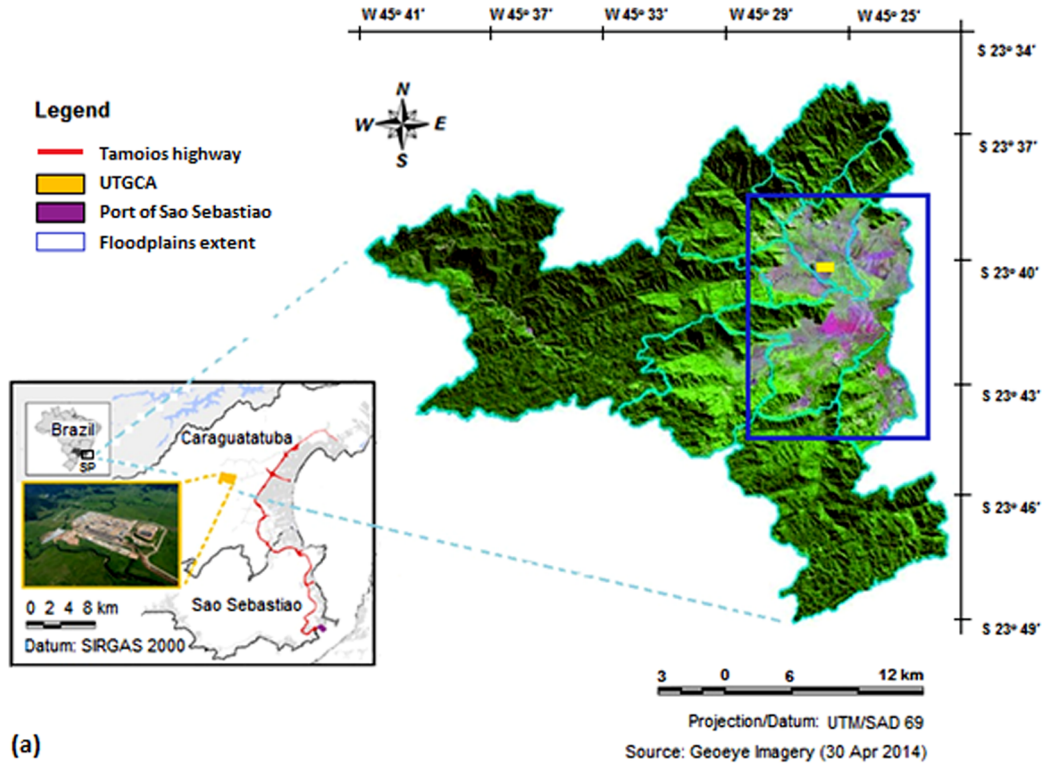


Fig. 2. (a) The floodplains of the Juqueriquere river basin and the main infrastructure developments, (b) the distribution of rivers in each subbasin of the Juqueriquere river basin.

regions are affected by frequent episodes of inundation in the Juqueriquere river basin [36] (Fig. 2b).

After the historical development of agricultural activities, an emerging economic and political speculation has been raised for the local land use and land cover (LULC) change, particularly after the establishment of the gas exploration plant (UTGCA) in 2012. Other infrastructure developments, such as the Tamoios highway and the Port of Sao Sebastiao (about 20 km from the plains) also motivated the urbanisation of the area [15], despite its vulnerability to natural disasters [37].

On the 18th of March 1967, the daily rainfall was 240.8 mm. In that year, the annual rainfall was 2141.2 mm. After more than 13 h of extreme rainfalls, debris flows from the saturated steep slopes devastated the area. In Caraguatatuba, more than 436 people lost their lives, and about 3000 inhabitants had their houses destroyed. After 50 years, it is still considered the most destructive natural disaster in the State of Sao Paulo [38].

3.2. Proposed methodology

Two main phases were carried out in the study: (1) the criteria selection and attribution by the expert-based survey (Delphi method), (2)

the weighting and ranking of hierarchical criteria (AHP). The methodological approach is shown in Fig. 3.

3.2.1. The expert-based survey: Delphi method

The fundamental objective of the survey was to evaluate the physical and hydrological criteria that affected the flood susceptibility in the neighbouring urban coastal and riverine area of the Juqueriquere plains. The decision-framing was incorporated in the first phase when the experts iteratively attributed criteria in accordance with the approach used in the study. In the thorough expert-based survey, there were three rounds: two anonymous rounds with the general experts using video conferences or individual interviews, and one round divided into parts I and II with the hydrology experts in a DM conference.

At first, 22 general experts were invited to take part in the survey, but only 15 were available to take part in both rounds. Their careers were in the field of geography, hydrology, meteorology, ecology, oceanography, civil, agricultural, survey and environmental engineering. In the first round, a pre-elaborated form (brainstorming criteria) was presented to the general experts for the initial brainstorm. It was based on the study area physical features, available hydrological modelling parameters and a previous

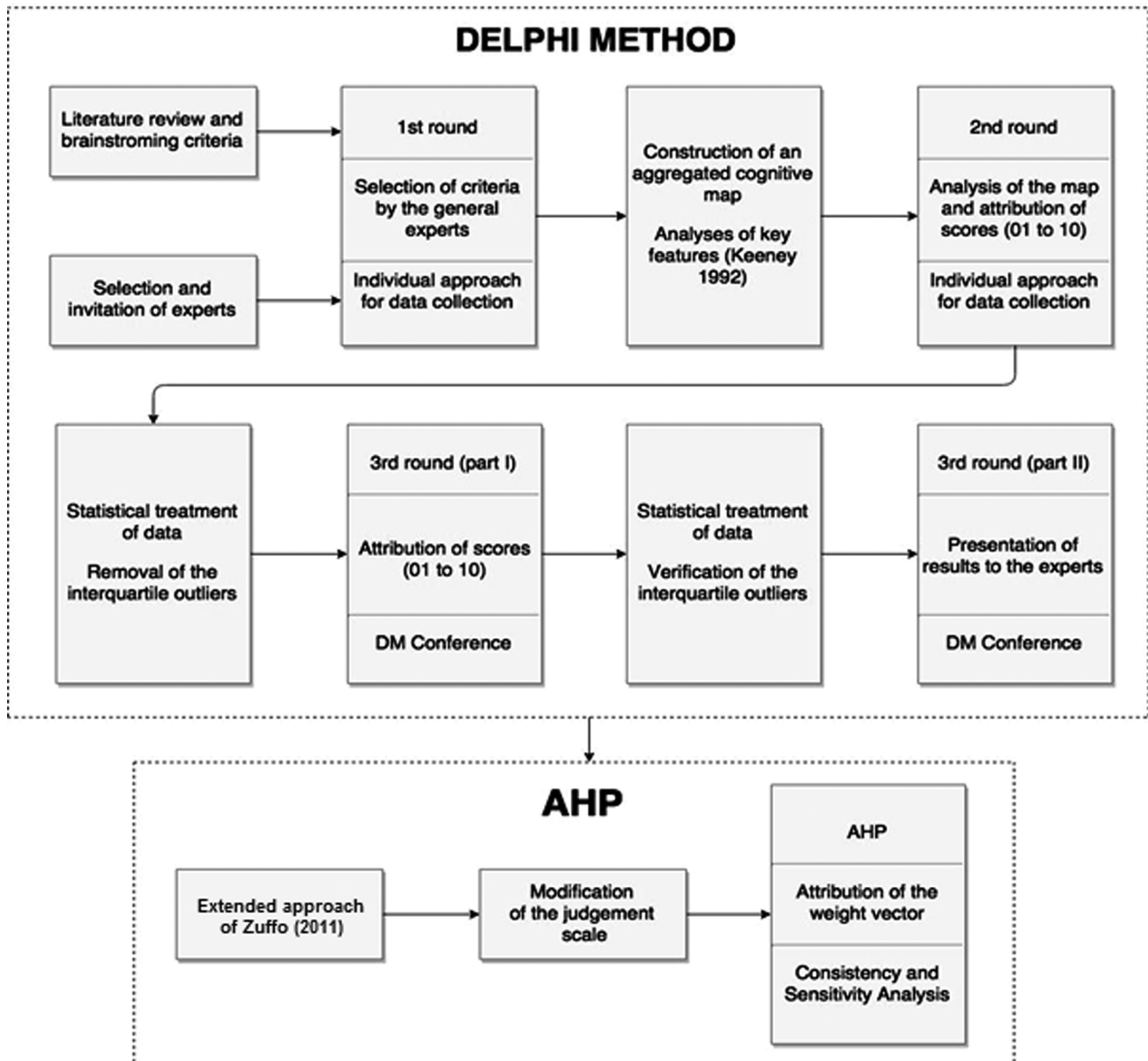


Fig. 3. Methodological procedure adopted in the study.

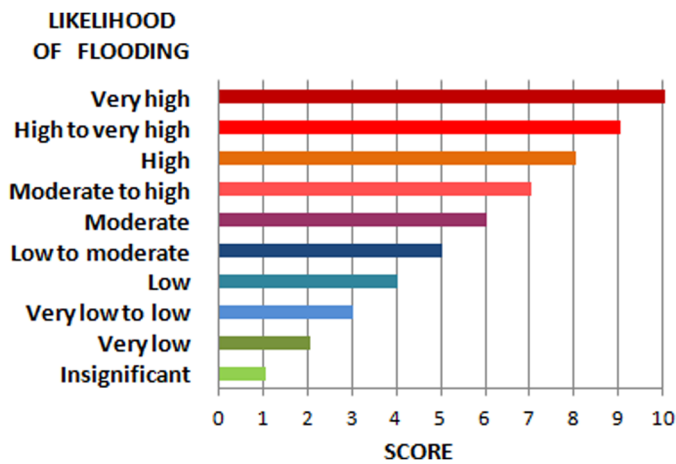


Fig. 4. Scores attributed to each criterion for the likelihood of flooding.

literature review: [2,3,5,13,39-41]. Additional criteria were suggested, while others were considered insignificant by the experts and thus, they were removed. The interview used a guided sequence of questions for each criterion (with “how” and “why” questions), according to [21].

An aggregated cognitive map was prepared with all the discussed criteria and presented to the experts in the 2nd round. Between the 1st and the 2nd rounds, all the criteria were analysed based on the key features defined by [19] and on the constraints of the study. The analysis was presented to each expert in the 2nd round to achieve a consensual outcome. Furthermore, they attributed scores from 1 to 10, according to the likelihood of each criterion to affect the flood susceptibility as shown in Fig. 4.

Between the 2nd and 3rd rounds, the criteria scores were statistically treated. The mean and quartile (Q1 and Q3) values were calculated, to measure the variation of each scored criterion. All the outliers out of the

quartile ranges were removed, according to the Delphi method approach. The 3rd round was carried out in a DM conference, attended by five hydrology experts. Part I started with an initial discussion about the concepts of the previously selected criteria, and then each expert wrote anonymous criteria scores based on the importance level. The scores were collected and immediately computed to achieve the final mean values for each criterion. In part II, the final results were presented to the hydrology experts.

3.2.2. The criteria weight ranking: AHP

After the attribution of scores by the experts, the mean value was used to assess the behaviour of the data set. The AHP extended approach of [25] was then applied. The root square judgement scale [24] was adopted based on the prior dispersion analysis of the dataset, as it is the most sensitive scale considering the consistency aspect and provides the most uniform allocation of priority values. Later, the linear judgement scale [29] was also used for comparison purposes to evaluate the consistency sensitivity and the variation of priority-value allocation among the criteria.

In the AHP approach, the pairwise judgement matrix was initially normalised. Then the vector matrix was found and also normalised, resulting in the weight vector matrix. Furthermore, the matrix highest eigenvalue was derived, and the consistency index and ratio could be determined.

A final sensitivity analysis was carried out by increasing and decreasing the most dominant criterion and evaluating if the other criteria varied accordingly. Several approaches to analyse the sensitivity of the AHP are found in literature [42,43]. In this study, the purpose was not to study the particularity of the sensitivity analysis but to use it as a tool to evaluate the coherence of the model towards the hierarchy order and weight vector.

4. Results and discussion

4.1. Criteria selection

The objective of the survey was to explore and select criteria that

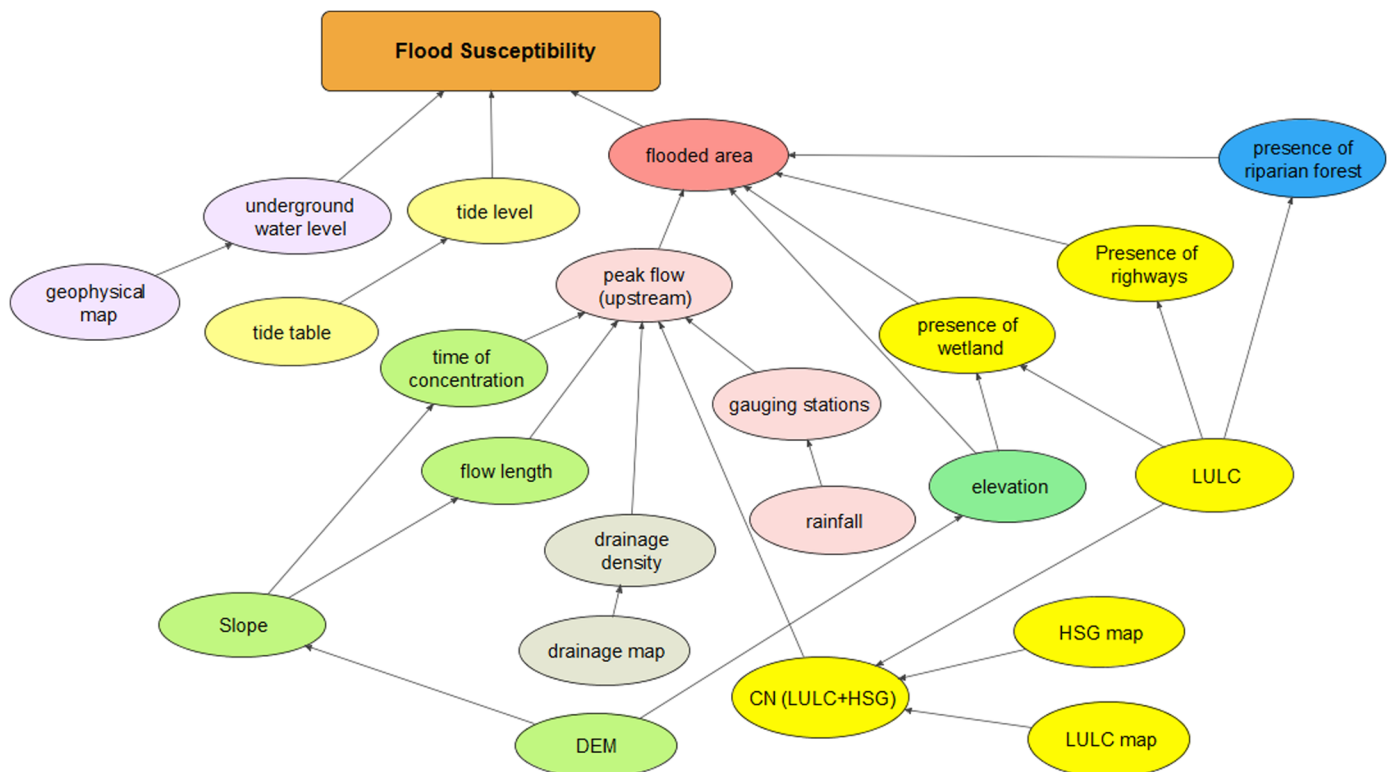


Fig. 5. Cognitive map of the aggregated criteria discussed with the experts in the 1st round. Note: CN = Curve Number, LULC = Land Use and Land Cover, HSG = Hydrological Soil Group.

affect the flood susceptibility in the study area. Floods frequently occur in the region, showing the natural vulnerability of the plains of the study area to this phenomenon. Thus, the questions raised by the experts were: What criteria mostly affect the flood likelihood in the study area? How much does each criterion affect the response of the watershed to floods?

The constraints of the study were that the criteria had to be physically related, or originated by hydrological phenomena. Besides, the data had to be available or feasible to estimate. The brainstorming criteria were also brought up at the discussion with the experts, who suggested the addition of new ones (refer to Table A1 in the Appendix). Finally, after interviewing all the available experts, the cognitive map of the aggregated criteria was drawn (Fig. 5), enabling the evaluation of the key features of [19] and to assess if the criteria were conclusive to be considered in the current study.

In the 2nd round, the aggregated cognitive map was presented to the experts. All the important concepts about each of the criteria and the evaluation of the key features [19] were taken into consideration. The means to achieve the criteria were also approached and the final decision was made. The concepts and evaluation of the attributed criteria (in the highlighted rows) are presented in Table 3.

Table 3
Evaluation of the criteria discussed in the 2nd round.

Criteria	Concepts raised in the survey	Evaluation
Curve number (CN)	It is a variable used in hydrological modelling, that associates the land use and land cover (LULC) change, the soil type and its infiltration conditions. [44] proposed a methodology to achieve the CN based on Brazilian types of soils and the underground water level.	This criterion was considered appropriate to be used in the study. The LULC and (Hydrological Soil Group) HSG raster maps are achievable input data. In the study area, some samples of a geological underground water survey [45] might also be used to infer the hydrological soil behaviour.
Drainage density (Dd)	According to [46], the Dd affects the concentration time and thus, the peak flow, as the flow velocity is increased in the river network.	This criterion was judged appropriate to be used in the study. It might be achieved through the river network of Sao Paulo [47].
Elevation	Low lying areas, where the DEM cells have lower elevation, are naturally susceptible to flow accumulation [2]. In coastal areas, these areas are also more affected by the high tide [3].	This criterion was considered appropriate to be used in the study. It might be achieved through a Digital Elevation Model (DEM), which is available for the study area.
Flow length	It is the distance of the flow from any point of the basin to the outlet. The lag time of the basin is represented by the division of the flow length by the flow velocity, which concerns the contribution of the basin towards the outlet.	This criterion is not appropriate as it is not decomposable from the slope. In a Geographical Information System (GIS), the equivalent flow length is calculated in a similar way to the slope of a segment. It is not operational and not concise either, as the value depends on the selected segment. Moreover, it should not be used in the study.
Peak flow (upstream)	The peak flow is related to the occurrence of rainfalls. The level of water in rivers rises when there are heavy rainfalls.	It is not decomposable from the rainfall or operational. As the basin is ungauged, there is no representative data available. So, this element should not be used in the study.
Presence of highways	It refers to the presence of highways and how it affects the drainage system in the surrounding area.	This is a redundant criterion, as it is achieved by the use of a LULC map. It is not operational either. As there is no micro or macro drainage plan for the area yet, nothing can be inferred about the drainage. Thus, it should not be used in the study.
Presence of riparian forests	It refers to the presence of riparian forest (vegetation situated on the banks of a river) and how it affects the discharge, roughness and infiltration along the length of the rivers.	This is a redundant criterion, as it is achieved by the use of a LULC map. The same area is classified and converted to a CN value, which takes into consideration the soil infiltration of the respective LULC class. Moreover, it should not be used in the study.
Presence of wetlands	It refers to the areas where there is a natural flow accumulation, especially in the rainy season.	This is a redundant element, as it is achieved by the use of a LULC map. The same area is classified and converted to a CN value, which takes into consideration the soil infiltration of the respective LULC class. Thus, it was judged inappropriate for the study.
Slope	It influences the direction and the total area available for the surface runoff. It contributes essentially to the duration of the surface flow, infiltration and subsurface flow [2].	Appropriate to be used in the study. It might be achieved through geoprocessing techniques applied to a DEM, which is available for the study area.
Rainfall	Heavy rainfalls are the triggering cause of floods. As the plains of the study area are surrounded by high and steep mountains, they are also affected by orographic rain.	This criterion is appropriate to be used in the study. Data is available from rain gauges distributed around the basin. Thus, geoprocessing techniques and spatial analysis will be necessary for the rainfall interpolation.
Tide level	The plains of the study area are in a coastal low lying region. This criterion refers to how tide level could affect the flow in the river network.	There is no data recorded in the field regarding how different the dispersion of the tide is throughout the plains. Then, this element is not operational, and not measurable, as there are no available data. Consequently, it may not be applied in the study.
Time of concentration	It is the average time need for the water to flow towards the outlet of the basin. The calculation might use different equations, which mostly use the slope and area as input variables. The equation is chosen based the LULC and area.	The element is not decomposable from the slope. It is not concise, because If the sub-basins are divided into smaller portions, other equations have to be applied, providing different results. Therefore, it is inappropriate to be used in the study.
Underground water level	It refers to the natural infiltration condition of the soil. When the saturation level is high, the infiltration decreases.	There is no representative data available. As it is not achievable for the time being, it was considered not measurable and judged as inappropriate for the study.

4.2. Score attribution

After achieving a consensual outcome regarding the criteria that should be removed, the general experts assigned a score to the selected criteria (refer to Table A2 in the Appendix). Between the 2nd and the 3rd round, the data were statistically analysed, according to the Delphi method. All the quartile outliers were removed. In the 3rd round, five hydrology experts took part in the DM conference. In part I, the aggregated cognitive map was presented, and there was a consensual outcome about the appropriate criteria to be used. Then, each of the experts individually assigned the respective scores.

The scores were collected, and the statistical treatment was done before part II. There were no outliers among the scores given by the hydrology experts. Further, the final results were presented and approved (refer to Table A3 in the Appendix). The scores of the 2nd and 3rd rounds and the hierarchy variation among the criteria are shown in Table 4.

After the statistical treatment of both rounds, the deviation between the most and least dominant importance levels slightly changed. In the 2nd round, the deviation was 0.67, and in the 3rd round, it was 0.52. The criteria were constrained in the range between 8 and 9 (in a scale

Table 4
Criteria score and hierarchy in 2nd and 3rd rounds.

Criteria	2nd Round	Hierarchy	3rd Round	Hierarchy
CN	8.20	4	8.43	4
Dd	8.87	1	8.80	2
Elevation	8.67	2	8.88	1
Rainfall	8.53	3	8.50	3
Slope	8.20	4	8.36	5

out of 10) in both rounds. This is one of the peculiarities of the Delphi method outcomes, i.e. to be in a limited range due to the removal of the quartile outliers (see the 3rd paragraph of item 2.2 - Delphi method). The variation of hierarchy was observed between the 1st and 2nd most dominant criteria (elevation and Dd). Regarding the weakest ones (i.e. CN and slope), they were both in the 4th position after the 2nd round and then they were allocated in the 4th and 5th positions, respectively, after the 3rd round.

4.3. Hierarchical process

The first step after the score attribution was to analyse the dispersion of the data (Fig. 6). Even though the range was limited, there were two evident clusters. The first was with the two most dominant criteria and the other with the three least dominant ones. One of the features of the root square judgement scale [24] is that the weight allocation might be smoothly distributed in disperse data sets. Thus, this scale was the one used in the AHP.

The extended AHP approach of [25] was carried out, generating the pairwise comparison matrix with the root square judgement scale. The further AHP steps were conducted until the normalised weight vector was obtained (refer to Table A4 in the Appendix). The same procedure was developed using the linear judgement scale [29] up to the consistency evaluation. The comparison results are presented in Table 5.

The root square judgement scale showed more consistent results than the linear scale for the CI and CR which were both less than 0.1

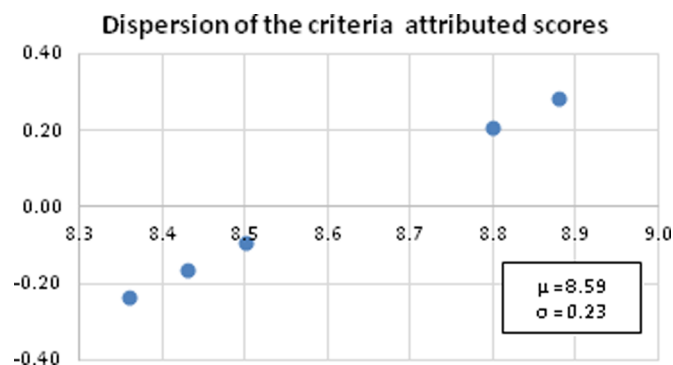


Fig. 6. Analysis of the dispersion among the criteria scores.

Table 5
Results of the pairwise comparison carried out in the study using both linear and root square judgement scales.

Criteria	Criteria weight	
	linear	root squared
Elevation	10.00	10.00
Dd	7.42	7.72
Rainfall	3.04	4.25
CN	2.06	3.21
slope	1.39	2.45
Consistency Evaluation	CI	0.0503
	CR	0.0449

Table 6
The sensitivity analysis of the two different scenarios.

Criteria	Weight vector (current scenario)	Weight vector (Elevation + 10%)	Weight vector (Elevation - 0.5%)
Elevation	10.00	10.00	10.00
Dd	7.72	5.14	8.72
Rainfall	4.25	3.48	4.38
CN	3.21	2.96	3.31
Slope	2.45	2.57	2.53
Consistency Evaluation	CI	0.0244	0.0151
	CR	0.0218	0.0135

and closer to zero. The allocation of priority values was also smoother for the root square judgement scale. The discrepancy of values allocated to the 2nd most dominant criterion (Dd) was not high, but very significant compared to the weakest criteria (Rainfall, CN and slope). Therefore, the selection of the root square judgement scale for the AHP in the study was corroborated.

At last, the sensitivity analysis (SA) was carried out by the evaluation of two different scenarios: the increase of 10% and the decrease of 0.5% of the most dominant score. The decrease was of 0.5% as there was only a deviation of 1% between the 1st and 2nd most dominant criteria. If more than 0.5% was deducted, a hierarchical change would occur in the AHP. As there were no significant differences noticed at the results of the SA within the two testing scenarios, the methodology applied in the study might be considered consistent. The final outcomes are shown in Table 6 and the complete AHP matrices using the two sensitivity testing scenarios are displayed in the Appendix on Tables A5 and A6.

In both scenarios, there was no change in the hierarchical order. As expected, the values of the 2nd most dominant criterion were modified, but a slight discrepancy occurred in the three least dominant criteria. The model was also consistent for the two different scenarios.

In future works, the selected criteria might be implemented in a GIS model to simulate the response of the basin in different scenarios. The numerical value of each criterion may vary in different periods of time but the criteria weights, which were selected in this study, will remain the same. For instance, pretending that the CN is currently 70, due to a LULC of a forest in a HSG of type C, and in the future the CN becomes 90 (after the urbanisation process), the criteria weight to be inserted in the GIS model will still be 3.31 for both scenarios (i.e. for $CN_1 = 70$ and $CN_2 = 90$), but the value of the criterion CN will vary from 70 to 90. However, if the effect of each criterion changes or even more criteria start affecting the response of the basin to floods, the methodology of this study has to be carried out again and updated weights need to be attributed.

5. Conclusions

In the current study, we presented the expert-based survey by the use of the Delphi method, which was enhanced by the cognitive map of the aggregated criteria and the evaluation of the key elements of [19]. The outcomes were consensual, and the common respondents' biases that normally occurs in DM surveys could be avoided. The judgement of all experts was statistically treated, resulting in a limited range of weights (8.36 to 8.88). Moreover, the use of the extended AHP approach of [25] was effective to convert this restricted scale to a wide range of priority values.

We proposed the use of the root square judgement scale [24], which provided a better consistency than the linear scale [29]. The final criteria weights were also better distributed, especially for the three least dominant values. By the use of the linear scale, the criteria weights had a similar behaviour to the initial ones (assigned by the experts), which

were split into two main clusters: one with the two most dominant weights and the other with the three least dominant weights. Consequently, the root square judgement scale [24] enhanced the AHP outcomes of the study model.

Lastly, the sensitivity analysis demonstrated the coherence of the weight vector. The simulation of different scenarios by the modification of the most dominant criteria only affected the final weights but not the hierarchy. The methodology proposed in the study was very useful to evaluate the consistency and the sensitivity of the model, providing reliable matrices and appropriate allocation of priority values.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.orp.2019.100116](https://doi.org/10.1016/j.orp.2019.100116).

Appendix

Table A1, A2, A3, A4, A5, A6.

Table A1
Criteria selected by the experts in the 1st round of the survey.

General Experts	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	votes	%	
Brainstorming criteria	CN	x	x	x	x	x	x	x	x	x	x	x	x	x	x	15	100	
	elevation	x	x	x	x	x	x	x	x	x	x	x	x	x	x	15	100	
	flow length	-	-	-	-	x	x	x	x	x	-	-	-	-	x	-	6	40
	peak flow (upstream)	x	x	x	-	-	-	-	x	-	-	x	x	-	-	-	6	40
	presence of highways	X	x	x	x	-	-	-	-	-	-	-	-	-	-	-	4	27
	presence of riparian forests	X	-	x	-	-	-	-	x	x	x	x	x	-	x	x	9	60
	presence of wetlands	X	x	x	x	-	x	-	x	x	-	x	x	-	-	x	10	67
	rainfall	X	x	x	x	x	x	x	x	x	x	x	x	x	x	x	15	100
	slope	X	x	x	x	-	x	x	x	x	x	x	x	x	x	x	14	93
	presence of riparian forests	X	-	x	-	-	-	-	x	x	x	x	x	-	x	x	9	60
	tide level	X	x	x	x	-	x	-	x	x	x	-	-	x	x	-	10	67
Suggested criteria	drainage density	X	-	-	x	x	x	-	x	x	x	x	x	-	x	x	11	73
	time of concentration	-	-	x	-	-	-	-	-	-	-	-	-	x	-	-	2	13

Table A2
Analysed criteria in the 2nd round.

Criteria	General experts															Statistical analysis		
	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	mean	Q1	Q3
CN	10	9	8	8	9	7	10	8	8	8	7	9	7	8	7	8.20	7.5	9.0
Dd	10	9	10	9	8	10	8	8	10	10	8	8	8	8	9	8.87	8.0	10.0
Elevation	10	10	9	8	8	10	10	8	10	9	8	7	7	7	9	8.67	8.0	10.0
Rainfall	10	8	9	8	8	9	10	8	8	8	8	9	9	8	8	8.53	8.0	9.0
Slope	10	10	8	7	7	9	8	8	8	8	9	8	9	7	7	8.20	7.5	9.0

Table A3
Analysed criteria in the 3rd round.

Criteria	General experts															Hydrology experts					Statistical analysis		
	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	01	02	03	04	05	mean	Q1	Q3
CN	-	9	8	8	9	-	-	8	8	8	-	9	-	8	-	8	9	9	9	8	8.43	8.0	9.0
Dd	10	9	10	9	8	10	8	8	10	10	8	8	8	8	9	8	10	9	8	8	8.80	8.0	10.0
Elevation	10	10	9	8	8	10	10	8	10	9	8	-	-	-	9	8	8	9	9	8	8.88	8.0	10.0
Rainfall	-	8	9	8	8	9	-	8	8	8	8	9	9	8	8	9	9	9	9	9	8.50	8.0	9.0
Slope	-	-	8	-	-	9	8	8	8	8	9	8	9	-	-	8	9	9	8	8	8.36	8.0	9.0

Note: (-) represents the quartile outliers (i.e. from the Q1 and Q3), which were removed from the 2nd round (refer to item 4.2 - Score Attribution).

Table A4
AHP matrices with the extended approach of [25] and the root square judgement scale [24] of the current scenario.

	Criteria	Elevation	Dd	Rainfall	CN	Slope
AHP extended approach of [25]	Weight	8.88	8.80	8.50	8.43	8.36
	Elevation	0.00	0.08	0.38	0.45	0.52
	Dd	–	0.00	0.30	0.37	0.44
	Rainfall	–	–	0.00	0.07	0.14
	CN	–	–	–	0.00	0.07
	Slope	–	–	–	–	0.00
Pairwise Comparison Matrix	Elevation	1.000	1.732	2.646	2.828	3.000
	Dd	0.577	1.000	2.450	2.646	2.828
	Rainfall	0.378	0.408	1.000	1.732	2.000
	CN	0.354	0.378	0.577	1.000	1.732
	Slope	0.333	0.354	0.500	0.577	1.000
	Total	2.642	3.872	7.173	8.784	10.561
Normalisation	Elevation	0.378	0.447	0.369	0.322	0.284
	Dd	0.219	0.258	0.342	0.301	0.268
	Rainfall	0.143	0.105	0.139	0.197	0.189
	CN	0.134	0.098	0.080	0.114	0.164
	Slope	0.126	0.091	0.070	0.066	0.095
	Eigin vector	Criteria	Mean	Vector V	Vector W	λ
	Elevation	0.360	1.8528	10.00	5.1443	
	Dd	0.277	1.4301	7.72	5.1542	
	Rainfall	0.155	0.7877	4.25	5.0850	
	CN	0.118	0.5947	3.21	5.0412	
	Slope	0.090	0.4532	2.45	5.0628	5.0975

Table A5
AHP matrices used for the SA considering the elevation weight + 10%.

	Criteria	Elevation	DD	Rainfall	CN	Slope
AHP extended approach of [25]	Weight	9.77	8.80	8.50	8.43	8.36
	Elevation	0.00	0.97	1.27	1.34	1.41
	Dd	–	0.00	0.30	0.37	0.44
	Rainfall	–	–	0.00	0.07	0.14
	CN	–	–	–	0.00	0.07
	Slope	–	–	–	–	0.00
Pairwise Comparison Matrix	Elevation	1.000	2.646	3.000	3.000	3.000
	Dd	0.378	1.000	1.732	2.000	2.000
	Rainfall	0.333	0.577	1.000	1.414	1.414
	CN	0.333	0.500	0.707	1.000	1.414
	Slope	0.333	0.500	0.707	0.707	1.000
	Total	2.378	5.223	7.146	8.121	8.828
Normalisation	Elevation	0.421	0.507	0.420	0.369	0.340
	Dd	0.159	0.191	0.242	0.246	0.227
	Rainfall	0.140	0.111	0.140	0.174	0.160
	CN	0.140	0.096	0.099	0.123	0.160
	Slope	0.140	0.096	0.099	0.087	0.113
	Eigin Vector	Criteria	Mean	Vector V	Vector W	λ
	Elevation	0.411	2.1021	10.00	5.1118	
	Dd	0.213	1.0810	5.14	5.0725	
	Rainfall	0.145	0.7313	3.48	5.0439	
	CN	0.124	0.6211	2.96	5.0242	
	Slope	0.107	0.5406	2.57	5.0507	5.0606

Table A6

AHP matrices used for the SA considering the elevation weight - 0.5%.

	Criteria	Elevation	DD	Rainfall	CN	Slope
AHP extended approach of [25]	Weight	8.84	8.80	8.50	8.43	8.36
	Elevation	0.00	0.04	0.34	0.44	0.48
	Dd	–	0.00	0.30	0.37	0.44
	Rainfall	–	–	0.00	0.07	0.14
	CN	–	–	–	0.00	0.07
	Slope	–	–	–	–	0.00
Pairwise Comparison Matrix	Elevation	1.000	1.732	2.646	2.828	3.000
	Dd	0.707	1.000	2.646	2.646	2.828
	Rainfall	0.378	0.378	1.000	1.732	2.000
	CN	0.354	0.354	0.577	1.000	1.732
	Slope	0.333	0.333	0.500	0.577	1.000
	Total	2.772	3.479	7.369	8.966	10.732
Normalisation	Elevation	0.361	0.406	0.359	0.315	0.280
	Dd	0.255	0.287	0.359	0.315	0.280
	Rainfall	0.136	0.109	0.136	0.193	0.186
	CN	0.128	0.102	0.078	0.112	0.161
	Slope	0.096	0.096	0.068	0.064	0.093
	Criteria	Mean	Vector V	Vector W	λ	λ_{\max} (average)
Eigin vector	Elevation	0.344	1.7631	10.00	5.1213	
	Dd	0.299	1.5382	8.72	5.1393	
	Rainfall	0.152	0.7730	4.38	5.0837	
	CN	0.116	0.5843	3.31	5.0336	
	Slope	0.088	0.4459	2.53	5.0496	

References

- [1] Jonkman SN, Dawson RJ. Issues and challenges in flood risk management - editorial for the special issue on flood risk management. *Water* 2012;4:785–92 <https://doi.org/10.3390/w4040785>.
- [2] Ouma YO, Tateishi R. Urban flood vulnerability and risk mapping using integrated multi-parametric AHP and GIS: methodological overview and case study assessment. *Water* 2014;6(6):1515–45 <https://doi.org/10.3390/w6061515>.
- [3] Shahapure SS, Eldho TI, Rao EP. Flood simulation in an urban catchment of Navi Mumbai City with detention pond and tidal effects using FEM, GIS, and remote sensing. *J Waterway Port Coastal Ocean Eng* 2011;137(6):286–99 [https://doi.org/10.1061/\(ASCE\)WW.1943-5460.0000093](https://doi.org/10.1061/(ASCE)WW.1943-5460.0000093).
- [4] Fenicia F, Savenije HH, Matgen P, Pfister L. A comparison of alternative multi-objective calibration strategies for hydrological modelling. *Water Resour Res* 2007;43(3) <https://doi.org/10.1029/2006WR005098>.
- [5] Tehrani MS, Pradhan B, Jebur MN. Flood susceptibility mapping using a novel ensemble weights-of-evidence and support vector machine models in GIS. *J Hydrol* 2014;512:332–43 <https://doi.org/10.1016/j.jhydrol.2014.03.008>.
- [6] Chowdhury RK, Rahman R. Multicriteria decision analysis in water resources management: the Malnichara channel improvement. *Int J Environ Sci Technol* 2008;5(2):195–204 <https://doi.org/10.1007/BF03326013>.
- [7] Chung ES, Lee KS. Prioritization of water management for sustainability using hydrologic simulation model and multicriteria decision making techniques. *J Environ Manage* 2009;90(3):1502–11 <https://doi.org/10.1016/j.jenvman.2008.10.008>.
- [8] Karimi AR, Mehrdadi N, Hashemian SJ, Bidhendi GN, Moghaddam RT. Selection of wastewater treatment process based on the analytical hierarchy process and fuzzy analytical hierarchy process methods. *Int. J. Environ. Sci. Technol.* 2011;8(2):267–80 <https://doi.org/10.1007/BF03326215>.
- [9] Vassoney E, Mochet AM, Comoglio C. Use of multicriteria analysis (MCA) for sustainable hydropower planning and management. *J Environ Manage* 2017;196:48–55 <https://doi.org/10.1016/j.jenvman.2017.02.067>.
- [10] Boulomytis VTG, Alves CD, Zuffo AC, Gireli TZ. Multi-criteria decision making for the assessment of coastal flood vulnerability. *Proceedings of the world environmental and water resources congress; 2015 May 17–21*. ASCE Press; 2015. p. 1248–55 <https://doi.org/10.1061/9780784479162.123>.
- [11] Horita FE, Albuquerque JP, Degrossi LC, Mendiondo EM, Ueyama J. Development of a spatial decision support system for flood risk management in Brazil that combines volunteered geographic information with wireless sensor networks. *Comput Geosci* 2015;80:84–94 <https://doi.org/10.1016/j.cageo.2015.04.001>.
- [12] Qi H, Altinakar MS. GIS-based decision support system for dam break flood management under uncertainty with two-dimensional numerical simulations. *J Water Resour Plann Manage* 2011;138(4):334–41 [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000192](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000192).
- [13] Yahaya S, Ahmad N, Abdalla RF. Multicriteria analysis for flood vulnerable areas in Hadejia-Jama'are River basin, Nigeria. *Eur J Sci Res* 2010;42(1):71–83.
- [14] Kain JH, Soderberg H. Management of complex knowledge in planning for sustainable development: the use of multi-criteria decision aids. *Environ Impact Assess Rev* 2008;28(1):7–21 <https://doi.org/10.1016/j.eiar.2007.03.007>.
- [15] Boulomytis VTG, Alves CD, Zuffo AC, Gireli TZ. How effective are the environmental planning tools towards the urbanization process of Juqueriquere river basin in Caraguatatuba, SP. *Revista Brasileira de Gestao e Desenvolvimento Regional* 2015;11(3):31–55 <http://www.rbgrd.net/revista/index.php/rbgrd/article/view/1964/463> [Accessed 10 August 2017].
- [16] Hong H, et al. Flood susceptibility assessment in Hengfeng area coupling adaptive neuro-fuzzy inference system with genetic algorithm and differential evolution. *Sci Total Environ* 2018;621:1124–41.
- [17] Runge MC, Walshe T. Identifying objectives and alternative actions to frame a decision problem. In: Guntenspergen GR, editor. *Application of threshold concepts in natural resource decision making*. New York: Springer; 2014. p. 29–43 https://doi.org/10.1007/978-1-4899-8041-0_3.
- [18] Keeney RL. Value-focused thinking: identifying decision opportunities and creating alternatives. *Eur J Oper Res* 1996;92(3):537–49 [https://doi.org/10.1016/0377-2217\(96\)00004-5](https://doi.org/10.1016/0377-2217(96)00004-5).
- [19] Keeney RL. *Value-focused thinking: a path to creative decision-making*. Cambridge: Harvard University Press; 1992.
- [20] Keeney RL. Developing objectives and attributes. In: Edwards RF, Miles Jr, Winterfeldt D von, editors. *Advances in decision analysis. From foundations to applications*. Cambridge: Cambridge University Press; 2007.
- [21] Gregory RS, Keeney RL. Making smarter environmental management decisions. *J Am Water Resour Assoc* 2002;8(6):1601–12 <https://doi.org/10.1111/j.1752-1688.2002.tb04367.x>.
- [22] Ferretti V. From stakeholders' analysis to cognitive mapping and Multi-Attribute Value Theory: an integrated approach for policy support. *Eur J Oper Res* 2016;253(2):524–41 <https://doi.org/10.1016/j.ejor.2016.02.054>.
- [23] Mendoza GA, Prabhu R. Evaluating multi-stakeholder perceptions of project impacts: a participatory value-based multi-criteria approach. *Int J Sustain Develop World Ecol* 2009;16(3):177–90 <https://doi.org/10.1080/13504500902919672>.
- [24] Harker P, Vargas L. The theory of ratio scale estimation: saaty's analytic hierarchy process. *Manag Sci* 1987;33(11):1383–403 <https://doi.org/10.1287/mnsc.33.11.1383>.
- [25] Zuffo AC. [Incorporation of fuzzy mathematics in multicriteria methods to describe subjective criteria in water resources planning: fuzzy-CP and Fuzzy-CGT] *Incorporação de matemática fuzzy em métodos multicriteriais para descrever critérios subjetivos em planejamento de recursos hídricos: fuzzy-CP e Fuzzy-CGT*. *Revista Brasileira de Recursos Hídricos* 2011;16(4):29–40 <https://doi.org/10.21168/rbrh.v16n4.p29-40>.
- [26] Garcia-Melon M, Gomez-Navarro T, Acuna-Dutra S. A combined ANP-Delphi approach to evaluate sustainable tourism. *Environ Impact Assess Rev* 2012;34:41–50 <https://doi.org/10.1016/j.eiar.2011.12.001>.
- [27] Wright JTC, Giovinazzo RA. [Delphi: a tool for the prospective planning]. *Delphi: uma ferramenta de apoio ao planejamento prospectivo*. *Caderno de Pesquisas em Administração* 2000;1(12):54–65.
- [28] Terrados J, Almonacid G, Perez-Higueras P. Proposal for a combined methodology for renewable energy planning. Application to a Spanish region. *Renew Sustain Energy Rev* 2009;13(8):2022–30 <https://doi.org/10.1016/j.rser.2009.01.025>.
- [29] Saaty TL. A scaling method for priorities in hierarchical structures. *J Math Psych* 1977;15(3):234–81 [https://doi.org/10.1016/0022-2496\(77\)90033-5](https://doi.org/10.1016/0022-2496(77)90033-5).
- [30] Shin YB, Lee S, Chun SG, Chung D. A critical review of popular multi-criteria decision making methodologies. *Issues Inf Syst* 2013;14(1):358–65 <https://pdfs.semanticscholar.org/e0c9/33ef52f301884437d62da6832ca3273578d5.pdf> [Accessed 08 June 2017].
- [31] Zhang L. Comparison of classical analytic hierarchy process (AHP) approach and fuzzy AHP approach in multiple-criteria decision making for commercial vehicle

- information systems and networks (CVISN) project [dissertation]. Lincoln: University of Nebraska; 2010<http://digitalcommons.unl.edu/imssediss/11> [Accessed 10 May 2017].
- [32] Franek J, Kresta A. Judgement scales and consistency measure in AHP. *Procedia Econ Finance* 2014;12:164–73[https://doi.org/10.1016/S2212-5671\(14\)00332-3](https://doi.org/10.1016/S2212-5671(14)00332-3).
- [33] Saaty TL. *The analytic hierarchy process*. New York: McGraw-Hill; 1980.
- [34] Ishizaka A, Labib A. Review of the main developments in the analytic hierarchy process. *Expert Syst Appl* 2011;38(11):14336–45<https://doi.org/10.1016/j.eswa.2011.04.143>.
- [35] Salo A, Hamalainen R. On the measurement of preference in the analytic hierarchy process. *J Multi-Criteria Decis Anal* 1997;6(6):309–19[https://doi.org/10.1002/\(SICI\)1099-1360\(199711\)6:6%3C309::AID-MCDA163%3E3.0.CO;2-2](https://doi.org/10.1002/(SICI)1099-1360(199711)6:6%3C309::AID-MCDA163%3E3.0.CO;2-2).
- [36] Boulomytis VTG, Alves CD, Zuffo AC, Gireli TZ. Watershed spatial discretization for the analysis of land use change in coastal regions. [Bulletin of Geodetic Sciences]. *Boletim de Ciencias Geodesicas* 2017;23(1):101–14<http://dx.doi.org/10.1590/s1982-21702017000100007>.
- [37] Souza CR, de G. [Morphometric sustainability of watersheds for the flood development in coastal areas]. Suscetibilidade morfometrica de bacias de drenagem ao desenvolvimento de inundações em áreas costeiras. *Revista Brasileira de Geomorfologia* 2005;6(1):45–61<http://dx.doi.org/10.20502/rbg.v6i1.38>.
- [38] Pombo CC. [50 years ago: after three days of continuous rainfall, caraguatutuba suffers the worst tragedy in its history]. Há 50 anos: após tres dias ininterruptos de chuvas, caraguatutuba sofreu pior tragédia de sua história. *Folha de Sao Paulo*; 2017<http://acervofolha.blogfolha.uol.com.br/2017/03/18/ha-50-anos-apos-tres-dias-ininterruptos-de-chuvas-caraguatutuba-sofreu-pior-tragedia-de-sua-historia/> [Accessed 19 March 2017].
- [39] Fernandez DS, Lutz MA. Urban flood hazard zoning in Tucumán Province, Argentina, using GIS and multicriteria decision analysis. *Eng Geol* 2010;111(1):90–8<https://doi.org/10.1016/j.enggeo.2009.12.006>.
- [40] Kazakis N, Kougiass I, Patsialis T. Assessment of flood hazard areas at a regional scale using an index-based approach and Analytical Hierarchy Process: application in Rhodope–Evros region, Greece. *Sci Total Environ* 2015;538:555–63<https://doi.org/10.1016/j.scitotenv.2015.08.055>.
- [41] Lawal DU, Matori AN, Hashim AM, Wan Yusof K, Chandio IA. Detecting flood susceptible areas using GIS-based analytic hierarchy process. In: proceedings of the 2012 international conference on future environment and energy - IPCBEE v.28. Singapore: IACSIT Press; 2012<http://ipcbec.com/vol28/1-ICFEE2012-F002.pdf> [Accessed 20 September 2017].
- [42] Chen Y, Yu J, Khan S. The spatial framework for weight sensitivity analysis in AHP-based multi-criteria decision making. *Environ model Softw* 2013;48:129–40.
- [43] Hill MJ, Braaten R, Veitch SM, Lees BG, Sharma S. Multi-criteria decision analysis in spatial decision support: the ASSESS analytic hierarchy process and the role of quantitative methods and spatially explicit analysis. *Environ Model Softw* 2005;20(7):955–76.
- [44] Sartori A, Genovez AM, Neto FL. Tentative hydrologic soil classification for tropical soils. In: Zhang C, Tang H, editors. *Advances in water resources and hydraulic engineering*. Proceedings of 16th IAHR-APD Congress and 3rd Symposium of IAHR-ISHS. Springer; 2009https://doi.org/10.1007/978-3-540-89465-0_37.
- [45] Waterloo Brazil Environmental Consulting. *Underground Water Assessment, Caraguatutuba/SP - PETROBRAS 2009*. Report 734.1871/09, II.
- [46] Pallard B, Castellarin A, Montanari A. A look at the links between drainage density and flood statistics. *Hydrol Earth Syst Sci* 2009;13(7):1019–29<https://doi.org/10.5194/hess-13-1019-2009>.
- [47] Water Resources Management Secretariat of Sao Paulo. *The Northern Coastline of Sao Paulo Basin Committee (CBH-LN). Drainage map of juqueriquere river basin (shape file)*. Caraguatutuba: CBH-LN; 2010.