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Sustainable risk management strategy selection using a fuzzy multi-criteria decision approach

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Abstract: While several studies focused on the evaluation of risk management strategies to select the sustainable ones using multi-criteria analysis, most of these studies did not necessarily dealt with the integration of uncertainties. In a context where uncertainties are inherent to natural hazards management decision-making process, the challenge is to systematically take uncertainties into account throughout the assessment process in order to avoid biased decisions. This paper attempts to tackle this challenge by suggesting a methodological approach based on the application of fuzzy multi-criteria decision-making methods. Uncertainties are addressed in two main ways. First, fuzzy AHP is used to estimate the importance of each of the evaluation criteria. Then, fuzzy weighted arithmetic mean method or fuzzy PROMETHEE are used to prioritize the strategies regarding the set of criteria, considering a compensatory or non-compensatory reasoning in order to derive final ranking. This approach is tested in a case study proposing sensitivity analysis in order to study the impact of the compensation phenomenon and the integration of uncertainty in the choice of a sustainable risk management strategy. This hybrid fuzzy multi-criteria decision approach provides a structured framework for identifying the most sustainable strategy under uncertainty.

Keywords: natural hazards; flood; sustainable risk management; decision making tool; fuzzy multi-criteria methods; uncertainty

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1. Introduction

Natural hazards are increasingly causing damage to communities and can be roadblocks to their sustainable development. The sustainable management of natural hazards, which is achieved through the implementation of strategies that enable a holistic response to risks, is currently one of the most significant challenges. Recent studies have shed light on sustainability assessment as a tool that can help decision makers decide which strategies they should or should not implement in an attempt to make risk management more sustainable [1-3]. The decision-making in sustainability strategies must evaluate several conflicting criteria in the optimization process.

Multi-criteria decision-making (MCDM) methods deal with the selection of alternatives with the highest degree of satisfaction according to the defined criteria. These methods are gaining popularity in risk management sustainability assessment because of their usefulness in resolving conflicts among criteria [4,5]. There is an extensive body of literature on MCDM methods, which can be categorized into two main approaches. The first one, referred to as the compensatory approach, includes methods that allow full compensation among the criteria, thus changing the problem essentially into a single criterion problem. By doing so, the weakness of a criterion could be hidden behind the strength of another one. The compensatory methods are often simple and understandable, the most common methods are Multi-Attribute Utility Theory (MAUT) and Analytic Hierarchy Process (AHP) [6]. Despite their ease of use, in the case of complex problems solving the compensability among criteria can be problematic because important information can be lost by such aggregation.

The alternate approach consists of assuming non-compensation between criteria and does not or partially approves trade-offs between criteria. An unfavourable outcome of a criterion cannot be offset by a favourable outcome of another one. This aggregation approach includes methods like PROMETHEE and ELECTRE. The main drawback of these methods is that they imply ranking options on the basis of their relative performance leading to possible computational problems caused by the increasing number of criteria or options as well as increased work time consumption, to the loss of information on the sustainability level of each option, and to possible ranking reversal between pairs of options [7,8].

A challenge for decision makers that use MCDM is that there are several methods available, which renders the choice of a specific method subjective. It has been stated that decision makers do not usually properly explain the drivers for their choice of a certain method instead of another. The choice of one particular method depends on the type of solution expected by the decision makers and their familiarity with one method compared to another [5]. In the absence of guidance on how to choose the appropriate method, MCDM can be misused, and decision makers misled.

In handling complex problems, one unavoidably encounters various types of uncertainty coming from the choice and the relative importance of the chosen criteria, the quality of input data, the lack of knowledge on the studied phenomena, the changing conditions, etc. [9-12]. As a result, the produced outcomes could also be associated with uncertainty. Whereas MCDM methods are useful in handling complex problems, there are still some drawbacks arisen from the fact that their use commonly requires crisp data. Classical MCDM methods face a weakness in adequately capturing the uncertainness of criteria values [13]. These approaches provide just a single value for the output variable of interest without any indication of the expected variation around this value, whilst the outcomes of complex problems are not necessarily deterministic [14]. Accounting for uncertainty in MCDM tools is an increasing need in order to render these tools most useful [15], and to enable rational decision-making. To address the problem of data-induced uncertainty in decision-making process, a recent trend is the use of fuzzy MCDM methods in which the uncertainness of data is represented by the means of fuzzy sets [16-18].

Selecting a risk management strategy is a critical task. The nature of the criteria involved in the decision, the associated uncertainty and the importance of this decision make this task complex rendering the prioritization of alternative management strategies highly risky. In this context, [19] suggested the use of formalized approaches to inform the decision-makers about the potential influence of uncertainty on the ranking of risk management alternatives with regard to their sustainability. This paper seeks to manage the complexity of decision-making under uncertainty by answering the following questions: Is the choice of risk management strategies impacted by the compensation phenomenon? Does integrating uncertainty improve the quality of decision-making associated with risk management?

This paper is a continuation of a previous work on the design of a methodological framework for the selection of the most sustainable risk management strategy [2]. The purpose here is to integrate uncertainty into the process of sustainability evaluation in order to capture its impacts of the final results and raise decision-makers' awareness on the potential variability of these results due to the influence of uncertainty. For this purpose, the paper introduces a methodological approach that allows the use of fuzzy data instead of crisp data within the sustainability assessment process in order to provide confidence levels for the resulting uncertain performance levels. From the fuzzy performance, decision makers can select the range of values that best reflects a given confidence level, and they can also specify their attitude as optimistic, pessimistic or moderate. The suggested methodological approach is flexible in order to conduct both compensatory and non-compensatory analyses. Thus, as one of the main contributions of this paper, decision makers are able to use the fuzzy weighted arithmetic mean method and fuzzy PROMETHEE and then compare the obtained final ranking results from both methods before selecting the most sustainable strategy. The goal is not to create a new fuzzy MCDM method but to suggest a methodological approach that allows the decision makers to deal with the main challenges one may encounter when assessing the sustainability of risk management strategies in an uncertain environment to make more robust decisions. Hence, the unique aspect of this paper is to present the uncertainty level to the decisions on prioritization of risk management strategies by using the suggested fuzzy multi-criteria decision approach. The latter is illustrated on a case study referring to flood management in a municipality located in the Moselle river watershed (Meurthe-et-Moselle County, France).

The remainder of this paper is organized as follows. The next section introduces the concept of sustainable risk management in the perspective of disaster risk reduction, and briefly discusses the state-of-the-art of decision-making under uncertainty in the area of risk management. It also provides a brief review of fuzzy sets theory. Section 3 describes the methodological approach. Section 4 depicts an application to a real case study and discusses the results. In section 5, the advantages and drawbacks of the methodological approach are discussed, and some conclusions are noted.

2. State of the art

The following sub-sections discuss theoretical aspects surrounding the suggested approach for the assessment of the sustainability of risk management strategies using fuzzy multi-criteria methods.

2.1. Sustainable risk management decision-making

Natural disasters annually cause deaths, people affected, environmental impacts and economic losses. Environmental studies predict an increase in the number and danger of this type of disasters. For example, 2017 was the second most expensive year in history in relation to natural disasters [20]. Natural disasters cannot be avoided, so efforts have been made to establish models and plans to manage the associated risks. Reference frameworks defining guidelines for action have been proposed for risk management. The Sendai framework for Disaster Risk Reduction focuses on four main lines of action: knowledge of disaster risk, governance and risk management, new resilience practices and improvements in the post-disaster phase and recovered [20]. This framework has been adapted to local contexts such as the case of Nepal, Peru and Uganda [21], and Germany [22]. Various authors have proposed disaster management models based on the definition of indicators. The type of indicators depends on the context, both the location and the type of disaster. Indicators are proposed for earthquakes [23], for managing climate change [24-25], for floods [26-27], for risk reduction in industrial infrastructure [28], and so on. All the studies agree that factors or criteria of different nature (social, natural, economic) should be evaluated and they seek to validate their proposed model based on the application in a case of study. Ivcevic *et al.* [20] carried out an exhaustive analysis of these models and their respective indicators, highlighting the importance of comparing the definition of these indicators with the opinion of the relevant local actors and, to improve the effectiveness of risk management measures, temporary indicators of at least three stages should be used: pre-disaster, response and post-disaster.

Risk management is a multifaceted process which is affected by the interplay of a lot of factors, and involves various stakeholders, competing alternative strategies as well as various trade-offs. In this regard, one shall increasingly refer to the currently advocated concept of sustainable risk management. An important factor to be incorporated in risk management decision-making is sustainability. Risk management decisions need to be sustainable in order to ensure the protection of the community against risk from the short to the long run with lowest economic, environmental, institutional, and social costs possible. Specifically, these decisions should focus on reducing damage and contribute to the broader goal of sustainable development of the community [29].

Sustainable risk management can be defined as the minimisation of damage caused by hazards and/or the enhancement of resilience in both people and buildings toward these hazards to promote economic efficiency, social well-being and equity, as well as environmental improvements in the long term [2]. The theoretical implication of this definition is the integrative consideration of performance indicators related to technical, economic, social, institutional and environmental aspects (even at different level of importance depending on the context). Indeed, the vulnerability of exposed systems to risk is an integral factor encompassing physical, economic, social, political and environmental aspects that allows understanding the real extent of the risk. Furthermore, according to Dube [30], sustainable reconstruction strategies should be based on build-back-better. Build-back-better strategies should consider restoring physical infrastructure, re-establishing social systems, and renewing livelihoods, economies and the environment [30]. Consequently, a sustainable management strategy is that one with desired performances in reducing disaster damage over time, and the one which contributes to improve or to maintain the sustainable development of the territory affected by the hazards. Further details on what it means, in the context of this paper, for a strategy to be sustainable can be found in [2]. The criteria and indicators in regard to which the sustainability of a strategy could be assessed are stated in the section 3.1.

2.2. Risk management decision-making and uncertainty

The definition of indicators allows for improved risk management by providing decision support, but there is one component that hinders this type of decision making: uncertainty [31]. Doyle et al. [32] carried out a review of literature on uncertainty associated with natural disaster management, concluding that uncertainty has different ways of being expressed, but it revolves around the decision-maker [32]. In decisions associated with evolutionary and unpredictable events, uncertainty increases due to the lack of knowledge that this situation generates in the decision-maker.

In the case of disaster risk management, uncertainty will be evident in the evaluation and choice of strategies (alternatives) and in the weighting to be assigned to each evaluation criterion (weighting vector). Uncertainty cannot be eliminated, so methods must be established to integrate it into the decision-making process. The literature reveals that very few studies attempted to account for uncertainty in the ranking of risk management alternatives. Some of the existing proposals are, amongst others: an integration of the uncertainty of criteria weights [33], a communicational model of uncertainty defining typologies [32], an analysis of the role of foresight to broaden the display of risk management indicators [34], a framework for ranking flood management alternatives taking uncertainty on the hazard assessment into account and using a spatial probabilistic framework [35], the definition of uncertain assumptions [31] and the integration of fuzzy measures [36-38]. A lot of studies also considered the uncertainty of sustainable performance values by using fuzzy methods [39-42]. The studies with fuzzy measures show interesting potential, however, they have been partially addressed using only one type of fuzzy method without counteracting the results. Moreover, Rosner *et al.* [43] pointed out that decision-makers are not necessarily served or are often poorly served with information about the impacts of uncertainty on their risk management decisions.

2.3. Fuzzy sets theory

Fuzzy sets enable the handling of the non-statistical uncertainty associated with the vagueness of information coming mainly from expert opinions [44]. These sets are based on the fuzzy theory introduced in [45]. Fuzzy logic interprets uncertainty in an approximate way, thus allowing a given value x to belong to a set of values with a level of truth, called the degree of membership, and range from 0 to 1. Consequently, fuzzy sets can be considered sets whose elements have a continuum of degrees of membership. Fuzzy sets may be of any form. The linear forms, such as the singleton, uniform, triangular, trapezoidal, and polygonal forms, are the most commonly used [46]. The fundamental features of a fuzzy set are:

- the core, which corresponds to the set of elements with a degree of membership equal to 1;
- the support, which is the set of all the elements with a degree of membership greater than 0;
- the height or the largest degree of membership attained by any element; and
- the α-cuts, which are the sets of elements with a membership equal to or greater than α. Each fuzzy set can be uniquely represented by the union of all of its α-cuts [45], which are equivalent to the respective confidence intervals about the uncertain data with a confidence level of $(1 - \alpha)$. The higher α ισ, the lower the confidence associated with the α-cut is. The existence of only one interval for every possible α-cut in a fuzzy set opens the door to performing fuzzy arithmetic operations.

Consider two trapezoidal fuzzy sets, $A = (a_1, b_1, c_1, d_1)$ and $B = (a_2, b_2, c_2, d_2)$. According to [45], the algebraic operations of these fuzzy sets based on interval arithmetic can be expressed by equations 1 to 5. Thanks to the statement that each fuzzy set can fully and uniquely be represented by its α-cuts, such calculus can be more intuitively performed on the α-cuts considering the infimum and the supremum of the associated confidence intervals. Trapezoidal fuzzy sets are used here to present algebraic operations because they represent the most common membership function shape (triangular one is a special case which has a unique value for its core instead of an interval), thus they are best suited to easily explain calculations made on the α-cuts of fuzzy numbers of any shape.

Addition of two fuzzy sets:

$$A + B = (a_1 + a_2, b_1 + b_2, c_1 + c_2, d_1 + d_2) \tag{1}$$

Subtraction of two fuzzy sets:

$$A - B = (a_1 - d_2, b_1 - c_2, c_1 - b_2, d_1 - a_2) \tag{2}$$

Multiplication of two fuzzy sets:

$$A \otimes B \approx (a_1 * a_2, b_1 * b_2, c_1 * c_2, d_1 * d_2) \tag{3}$$

Multiplication with a real number k:

$$k \otimes A = (k * a_1, k * b_1, k * c_1, k * d_1) \tag{4}$$

Division of two fuzzy sets:

$$A / B \approx (a_1 / d_2, b_1 / c_2, c_1 / b_2, d_1 / a_2) \tag{5}$$

The outputs of the arithmetic calculations on fuzzy sets are also fuzzy sets. Defuzzification is the process of transforming the obtained fuzzy set to a single crisp value. Many defuzzification techniques have been reported in the literature, such as the centre of gravity (COG) or centroid, bisector of the area, max membership or height, weighted mean, first-of- or middle-of- or last-of-maxima, and random choice of maxima methods. [47]. Each of these methods extracts different levels of information from the fuzzy sets and consequently may lead to different crisp values [48]. Naturally, there are trade-offs to each of them, and the selection of the defuzzification technique depends on the specificities of the case at hand.

3. Proposed methodology

As summarized by the flowchart in Figure 1, the hybrid methodological approach developed in this paper consists of six main stages.

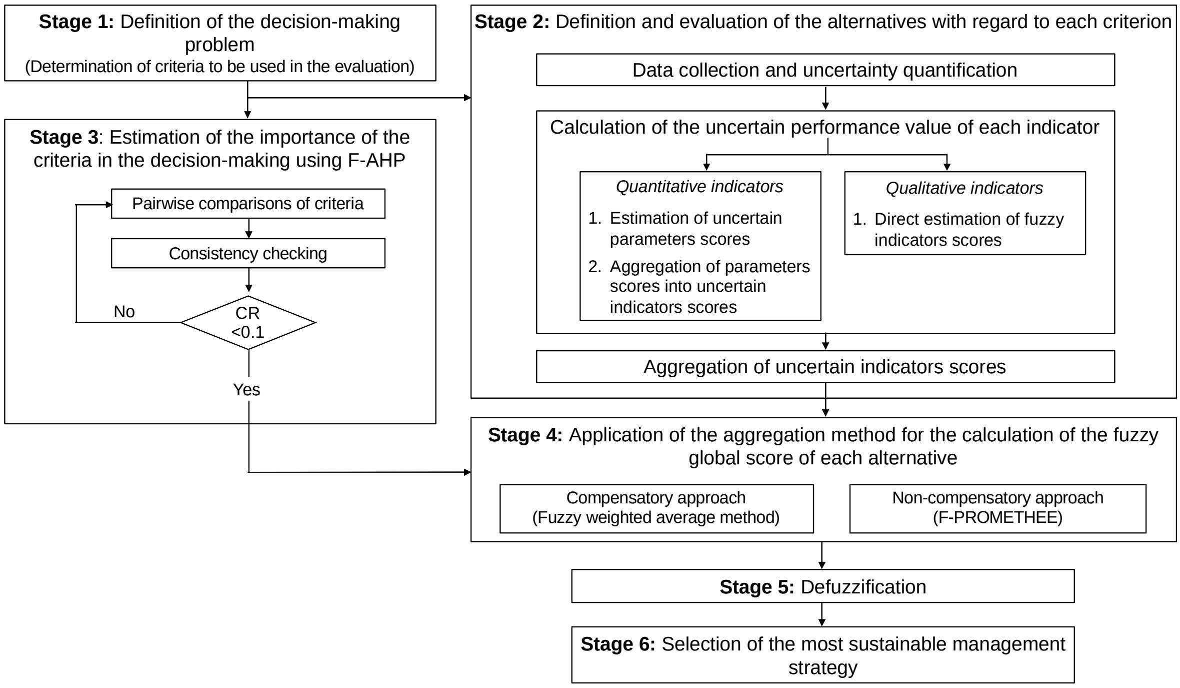

Figure 1. Schematic representation of the suggested approach

This approach relies on three different fuzzy MCDM methods. Each of these methods is intended for different purpose at a specific stage. F-AHP is used to account for uncertainty when estimating the weighs of the assessment criteria while fuzzy weighted average and F-PROMETHEE are retained for aggregating the uncertain criteria performance values and ranking alternatives. The use of AHP is fundamental for obtaining an input data for the application of other multicriteria methods: the weight vector. AHP allows to obtain this vector with a simple interaction with the decision-maker, besides evaluating the coherence of the answers given by the decision-maker. AHP allows the possibility of negotiation in case of integrating more than one decision-maker, generating different instances of discussion. Through a focus group to answer the comparison survey by pairs or by calculating a weight vector individually for each decision-maker and then from similarities and differences to obtain a weight vector representative of the group. However, the aggregation method to rank the alternatives gives a biased view, since it is based on the weighted average giving a compensatory ranking. Therefore, it was decided to complement the aggregation phase with both compensatory and non-compensatory views in order to strengthen the results obtained.

By comparing results from the latter two methods, decision-makers could analyze the impacts of the uncertainty stem from the choice of the aggregation approach on their decisions. As designed, the methodological approach allows accounting simultaneously for uncertainty arisen from (1) the opinions of stakeholders/experts on the relative importance of the criteria, (2) the performance value associated with each criterion, and (3) the choice between compensatory and non-compensatory aggregation reasonings. If the decision-makers do not choose a given aggregation approach, they will be served with information about the impacts of these kinds of uncertainty on the results from the sustainability assessment process.

3.1. Stage 1: Definition of the decision-making problem

In this first stage, the decision to be made must be clearly established. Subsequently, it should be structured as a decision-making problem. So, we must contextualize the problem by defining the criteria involved in the decision making. In this case, the problem is structured based on the study of [2]. They have identified five criteria split into indicators which can themselves be split into parameters depending on the specifics of the case under study (see Figure 2). The indicators are assumed to be heterogeneous in their nature: quantitative or qualitative. Quantitative indicators are assessed using data from numerical measurements, observations, statistical analyses of historical data or other sources such as modelling and simulations whereas qualitative ones rely on data resulting from experts' subjective judgments.

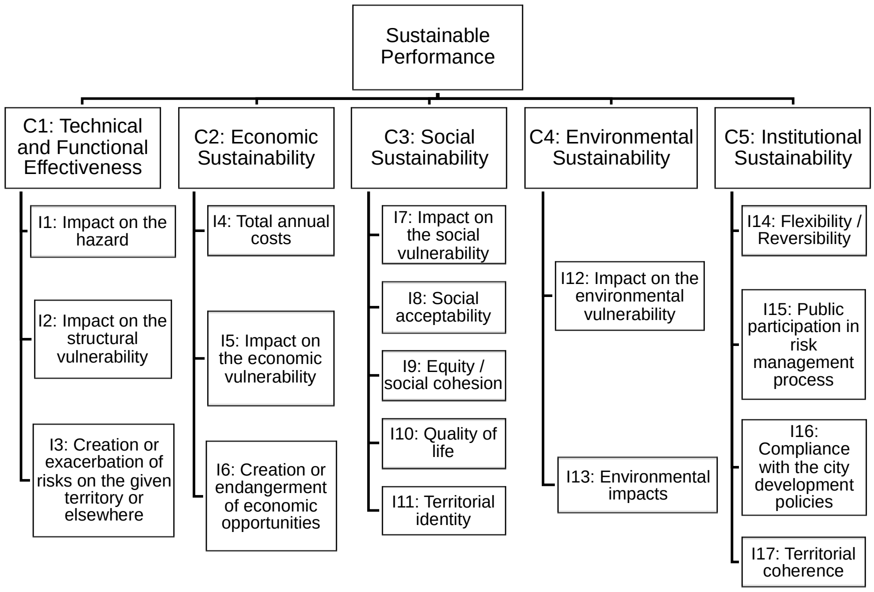

Figure 2. Hierarchical structure of the sustainability of natural risk management strategies

3.2. Stage 2: Definition and evaluation of alternatives with regard to each criterion

In the MCDM, the decision is made by choosing one option on a group of alternatives that answer the decision question. At this stage, we must define these alternatives that must be evaluated by all the criteria described in the previous stage. The evaluation framework consists of collecting data from different sources, determining uncertainty on each input data, representing the obtained uncertainty estimates, and computing the uncertain evaluations of criteria. The computation procedure is based on the sustainability assessment methodology introduced by [2] for crisp values. In this paper, the calculation equations have been adapted in order to enable accounting for data uncertainty and obtaining different criteria performance values associated with various confidence levels. The calculation procedure is not detailed herein as the ultimate goal of this paper is to emphasize the use of three different fuzzy MCDM methods (AHP to define the weighting of criteria, weighted average and PROMETHEE as methods of aggregation and ranking of alternatives) within an integrated approach. More detail about this calculation procedure can be seen in [49].

In short, as one of the main contributions of this paper, the decision-makers are able to use both quantitative and qualitative data as well as data that are known with certainty (crisp values) in association with those that are subject to uncertainty (sets of values, intervals, statistical distributions or polygonal fuzzy numbers). The results of the calculation procedure is a set of fuzzy intervals associated with a continuum of confidence levels that could be represented under the form of a single membership function, meaning that at the end of stage 2, the obtained performance values (called the criteria performance indexes, CPIs) of each alternative with respect to the five criteria are in the form of polygonal fuzzy numbers. This means that the CPIs calculation process could result in various fuzzy set shapes (single values or triangular, trapezoidal or polygonal fuzzy shape sets).

3.3. Stage 3: Estimation of the importance of the criteria in the decision-making using F-AHP

The first two stages define the characteristics of the problem without integrating the preferences of the decision-maker. The structure of the problem and the evaluation of the alternatives must be the same regardless of the decision-maker. In this third stage, the problem is adapted to the decision-maker or group of decision-makers based on the calculation of the criteria weighting vector. In a MCDM, the criteria could have different importance in the decision-making. This importance depends on the judgements of experienced experts or the preferences of stakeholders (including decision-makers) relying on the context of the study. In this paper, weights for the different criteria are allocated using fuzzy AHP (F-AHP) method. F-AHP is chosen as criteria prioritization method because it allows converting vague judgmental inputs (which are qualitative inputs) into quantitative inputs, in the form of weightage which will then be combined with the performance values for rating purpose.

The Analytic Hierarchy Process (AHP), which was developed by [50], is a method that provides a way to solve a problem by deriving relative priorities based on subjective judgments concerning the importance of the criteria and/or the extent to which the objectives described by the criteria are met by each alternative. F-AHP embeds fuzzy sets theory to the classical AHP, thus inheriting the advantages of both wherein the ability to use approximate information to generate decision as well as the relative ease to handle the combination of qualitative and quantitative data [13]. The key idea of F-AHP is that, in order to deal with the vagueness from their subjective perception, decision-makers usually come across with the fact that it is more secure to provide their judgments as intervals with a certain confidence level instead of crisp values [51]. As for the classical AHP, the main steps of F-AHP are as depicted in Figure 3.

This paper only considers step 2 dealing with the estimation of criteria weights. Experts are required to provide their judgments about the relative importance of each of the x criteria. Therefore, the result will be the obtaining of the weight vector that represents the importance of the criteria in the decision making. In classical AHP, the standard scale used is proposed by [50]. It is a 1 to 9 scale with 1 indicating that the two compared criteria have an equal importance, and 9 indicating that one criterion is extremely more important than the other.

Under fuzzy environment, comparison scales are described by membership functions which take on ranges of values. That is, preference expressed through the pairwise comparison is represented by a fuzzy number $\tilde{a}_{ij}$. Several fuzzy pairwise comparison scales, generally based on triangular where $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ or trapezoidal with $\tilde{a}_{ij} = (l_{ij}, m_{ij}, n_{ij}, u_{ij})$ fuzzy numbers, can be found in literature. Table 1 presents a triangular [52] and a trapezoidal [53] fuzzy numbers preference scales.

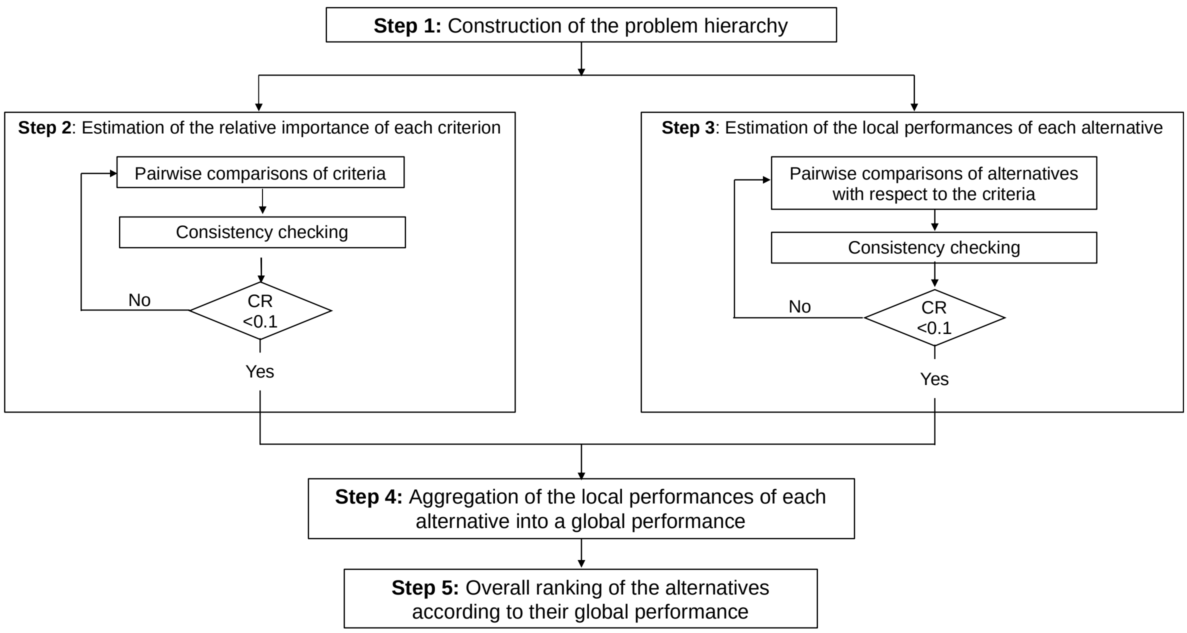

Figure 3. Main steps of the F-AHP method

Table 1. Sample of fuzzy pairwise comparison scales

		Comparison scales		
Intensity of importance	**Explanation of the judgement**	**Crisp value (Saaty's scale)**	**Fuzzy triangular number**	**Fuzzy trapezoidal number**

Exactly the same	If matrix diagonal	1	(1, 1, 1)	(1, 1, 1, 1)
Moderately more important than	I is slightly preferred to J	3	(1, 3, 5)	(1, 5/2, 7/2, 4)
Strongly more important than	I is strongly preferred to J	5	(3, 5, 7)	(4, 9/2, 11/2, 6)
Very strongly more important than	I is very strongly preferred to J	7	(5, 7, 9)	(6, 13/2, 15/2, 8)
Extremely more important than	I is extremely preferred to J	9	(7, 9, 9)	(8, 17/2, 9, 9)
Intermediate values between two adjacent scores	In the case of interpolating a compromise judgement	2, 4, 6, 8	(1, 2, 4); (2, 4, 6); (4, 6, 8); (6, 8, 9)	(1, 3/2, 5/2, 3); (3, 7/2, 9/2, 5); (5, 11/2, 13/2, 7); (7, 15/2, 17/2, 9)

As comparisons are made subjectively, the study of their logical consistency is crucial to avoid misleading results [54]. The Consistency Ratio (CR), on the basis of which it can be concluded whether the comparisons are sufficiently reliable or not, should not exceed a certain value. The threshold equals to 0.1 for a matrix with an order larger than 4 [55]. Before investigating the consistency of fuzzy pairwise comparison matrices, they need to be converted into crisp matrices. If the obtained crisp matrices are consistent, then the fuzzy matrices are also consistent [56]. Any of the existing defuzzification methods (see § 2.3) can be used for this purpose. Subsequently, the calculation and consistency analysis is carried out as proposed in the traditional AHP method.

A wide variety of procedures exist for calculating the relative weights of the criteria in the F-AHP method. The logarithmic least squares [57], geometric mean [58], synthetic extend analysis [59], fuzzy least-squares priority [60], direct fuzzification of the λ_{max} [61], fuzzy preference programming [62], and two-stage logarithmic goal programming [63] methods are some of these procedures. Buckley's geometric mean method, which is simple and easy to use, is adopted in this paper. This choice is due to the fact that this method is easy to the extend to the fuzzy case, it has a relative computational easiness, and guarantees a unique solution [64]. Thus, the following steps were taken relying on the work in the paper by [65] to determine the membership function for the criteria fuzzy priority weights.

- Calculation of the geometric mean (GM_i) of the fuzzy comparison values for criterion i compared to each of the other criteria equalling the geometric mean of each row (see equation 6), where n is the order of the matrix, and $\tilde{a}_{in}$ is the fuzzy comparison value for the pair of criteria i and n.

$$GM_i = (\tilde{a}_{i1} \otimes \tilde{a}_{i2} \otimes \tilde{a}_{i3} \otimes \ldots \otimes \tilde{a}_{in})^{1/n} \tag{6}$$

- Calculation of the fuzzy weight (W_i) of the i^{th} criterion according to equation 7.

$$W_i = \frac{GM_i}{(GM_1 + GM_2 + \cdots + GM_n)} \tag{7}$$

When instead of a single decision-maker, a group of stakeholders is involved in the judgement process, it is necessary to reach a consensus in order to obtain a weight vector representative of the group. AHP is a method that allows discussion and negotiation to achieve this consensus. Usually there are two instances of achieving consensus, at the time of filling out the pair-wise comparison survey or once the weight vector for each actor has been obtained. The first instance is generally done through a focus group, where in group responds to the survey, and the participation of a mediator is necessary to reach consensus in the discussion when responding to each comparison by pairs. The second instance is based on the analysis of the dispersion between the weights obtained by each actor for each criterion. If the dispersion is homogeneous, the arithmetic mean can be used as a consensus factor. If the dispersion is varied, other indicators such as the median or the mode can be used, among others. In this second instance, a negotiation can be carried out on the criteria that present the greatest dispersion, since these show which criteria generate the greatest doubt. When adopting the geometric mean method in group decision-making situations with m evaluators, the overall weight of criterion i (W_i) can be calculated as in equation 8 [66], where W^k_i represents the fuzzy weight given by the k^{th} evaluator. The obtained overall weights are defuzzified into crisp values, which are then normalised to easily compare the relative importance of the criteria: the larger a normalised weight is, the more important the corresponding criterion is.

$$W_i = (W^1{}_i \otimes W^2{}_i \otimes W^3{}_i \otimes \ldots \otimes W^m{}_i)^{1/m} \tag{8}$$

3.4. Stage 4: Application of the aggregation method for the calculation of the fuzzy global score of each alternative

Once the fuzzy criteria performance values and weights are known, the fourth stage of the suggested methodology consists of aggregating the individual evaluations of each criterion into a single global score by the means of a fuzzy MCDM method. Due to uncertainty arisen from the selection of decision rules we propose to address the application of the aggregation method for obtaining the global score based on two approaches: compensatory approach and non-compensatory approach. The objective is to obtain two alternative prioritization rankings, first considering the compensatory phenomenon and the other one without considering this phenomenon. If the same ranking is obtained, the result is strengthened to support decision-making, or if a different ranking is obtained, the alternatives affected by compensation are better understood and additional information is available for decision-making. Incorporating both approaches in the sustainability assessment process can contribute to a well-documented analysis in the strategic planning of risk management projects.

3.4.1. Compensatory approach: The fuzzy arithmetic mean method

The fuzzy arithmetic mean is an aggregation method that is commonly used in a number of MCDM problems. It consists of the calculation of the arithmetic average between fuzzy numbers (associated with fuzzy weights) by operating on the corresponding values in each fuzzy number at the same membership level [67]. To be completely accurate, the calculations have to be carried out using the α-cuts confidence intervals of the fuzzy numbers. Applying the fuzzy arithmetic mean method to a set of k numbers, $\tilde{a}_i = (l_i, m_i, n_i, u_i)$, with the assumption that these fuzzy numbers are equally weighted results in $\tilde{a} = (l, m, n, u)$ where:

$$l = \frac{1}{k}\sum l_i, \qquad m = \frac{1}{k}\sum m_i, \quad n = \frac{1}{k}\sum n_i \text{ and } u = \frac{1}{k}\sum u_i$$

The fuzzy weighted average is chosen as the aggregation method for the compensatory approach, since two of the most used compensatory methods such as AHP and MAUT use the weighted average to aggregate the assessments into an overall score. Therefore, using the weighted average in this case opens the option of using other compensatory methods with small variations.

3.4.2. Non-compensatory approach: The Fuzzy PROMETHEE method

Preference Ranking Organization METHod for Enrichment Evaluations (PROMETHEE) is an outranking method developed in the early 1980s by [68] to solve problems where a finite set of alternatives are to be ranked, and where incomparability takes place in most pairwise comparisons [69]. Ever since, several versions have been introduced for different usage as it could be seen in the literature. Further details on these methods can be found in [70]. PROMETHEE I and PROMETHEE II are the most commonly used versions [71]. However, according to [72], it seems easier to make decision by using complete instead of partial ranking. This paper focuses on PROMETHEE II. Consequently, hereinafter PROMETHEE and F-PROMETHEE refer to PROMETHEE II and its fuzzy extension, respectively. The main idea of PROMETHEE is to derive a ranking of alternatives from the best to the worst based on their positive/leaving $Ø^+$ (x), negative/entering $Ø^-$ (x), and net outranking flows Ø (x).

Since the crisp PROMETHEE methods have drawbacks arisen from their lack of ability to solve problems where there may be uncertainties, they have been combined with fuzzy sets leading to F-PROMETHEE methods [73-77]. As for classical PROMETHEE (see Figure 4), the stepwise procedure for F-PROMETHEE can be stated as follows. The starting step of PROMETHEE method is the construction of an evaluation table as shown in Table 2 where $C_j(a)$ is the evaluation of the alternative a with respect to the criterion j. This step results in the determination of partial binary relations presenting the strength of preference of an alternative over another.

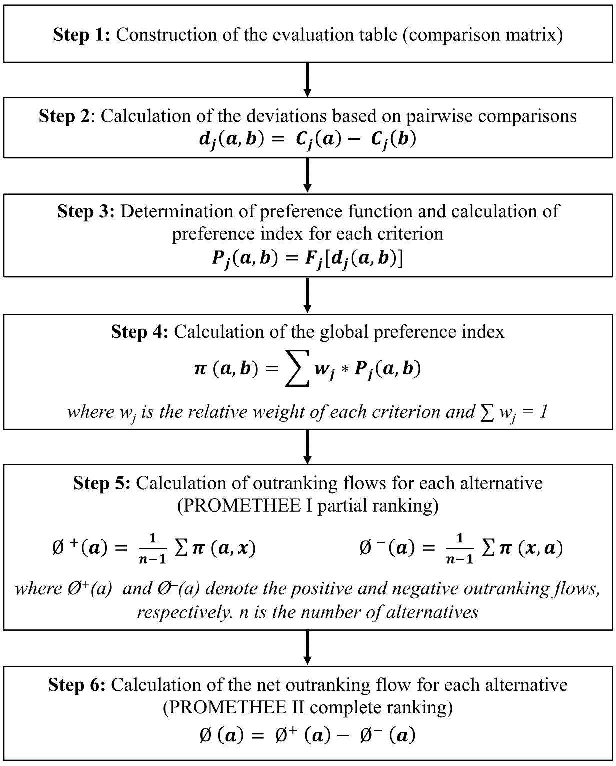

Figure 4. Sequential steps of the PROMETHEE II method

Table 2. Evaluation table

	Criteria				
Alternatives	**C1**	**C2**	**C3**	**…**	**Ck**
a	C_1 (a)	C_2 (a)	C_3 (a)		C_k (a)
b	C_1 (b)	C_2 (b)	C_3 (b)		C_k (b)
…	…	…	…	…	…
n	C_1 (n)	C_2 (n)	C_3 (n)		C_k (n)

Assuming that the evaluations of a and b with regard to criterion j are formulated as trapezoidal fuzzy numbers, $C_j(a) = (l_{aj}, m_{aj}, n_{aj}, u_{aj})$ and $C_j(b) = (l_{bj}, m_{bj}, n_{bj}, u_{bj})$, the deviation between the evaluations of a and b, $d_j(a, b)$, can be calculated as in equation 9.

$$d_j(a,b) = C_j(a) - C_j(b)$$

$$d_j(a,b) = (l_{aj} - u_{bj};\ m_{aj} - n_{bj};\ n_{aj} - m_{bj};\ u_{aj} - l_{bj}) \quad (9)$$

Then, the preference function translates the difference between the evaluations of two alternatives into a preference degree ranging from 0 to 1. It reflects the preference level of a over b in the interval [0; 1]. Six basic types of preference functions have been proposed in the literature by [78]. These are the usual, U-shape, V-shape, level, V-shape with indifference and Gaussian functions. The application of a given type of function depends on the problem [79] or the decision maker's preference, and it is possible to choose a different function for each criterion [80].

The preference index, $P_j(a, b)$, which denotes the preference of a in comparison with b for criterion j, is calculated as a function of $d_j(a, b)$ via equation 10. The value of $P_j(a, b)$ ranges from 0 to 1, and $P_j(a, b) = 0$ indicates that there is indifference between a and b (or no preference of a over b); additionally, $P_j(a, b) = 1$ indicates a strict preference of a over b.

$$P_j(a,b) = F_j[(l_{aj} - u_{bj};\ m_{aj} - n_{bj};\ n_{aj} - m_{bj};\ u_{aj} - l_{bj})]$$

$$P_j(a,b) = \left(F_j\left(l_{aj} - u_{bj}\right), F_j(m_{aj} - n_{bj}), F_j\left(n_{aj} - m_{bj}\right), F_j(u_{aj} - l_{bj})\right)$$

$$P_j(a,b) = \left(l_{ab}^j, m_{ab}^j, n_{ab}^j, u_{ab}^j\right) \tag{10}$$

Ideally, the preference function should be defined on the basis of consultations with the decision-maker, however, this additional step makes the application of the method more complex, especially when the decision-maker is a group of people. To overcome this limit the method normally works with hypotheses to define the preference function, the two most used hypotheses are the strict preference function, no matter the difference between alternatives the best evaluated alternative is always fully preferred. The other hypothesis is a linear increasing function, which says that the greater the difference between alternatives the greater the preference for the best evaluated alternative. The second hypothesis needs precision and certainty of the difference of evaluation between alternatives so its effectiveness could be reduced due to the uncertainty associated with the problem, so we decided to use the first hypothesis of strict preference function.

The usual function is indifference threshold free. With this function, $F_j\,[d_j(a, b)] = 0$ when $d_j(a, b) \leq 0$, and $F_j\,[d_j(a, b)] = 1$ when $d_j(a, b) > 0$. The global preference index represents the intensity of preference of a over b considering all the criteria simultaneously. The fuzzy global preference index $\pi\ (a, b)$ is calculated as in equation 11 with the assumption that the relative weights of the criteria are also trapezoidal fuzzy numbers $W_j = (l''_j, m''_j, n''_j, u''_j)$.

$$\pi\,(a,b) = \sum w_j \otimes \left(l_{ab}^j, m_{ab}^j, n_{ab}^j, u_{ab}^j\right)$$

$$\pi\,(a,b) = \sum \left(l_j'', m_j'', n_j'', u_j''\right) \otimes \left(l_{ab}^j, m_{ab}^j, n_{ab}^j, u_{ab}^j\right)$$

$$\pi\,(a,b) = \left(l_{ab}^\pi, m_{ab}^\pi, n_{ab}^\pi, u_{ab}^\pi\right) \tag{11}$$

The leaving and entering outranking flows for each alternative are computed using equations 12 and 13 with x = (b, c, d, …), respectively. A leaving flow $\emptyset^+(a)$ indicates the preference of alternative a over all the other (n – 1) alternatives. An entering flow $\emptyset^-(a)$ indicates the preference of all other (n – 1) alternatives over a. The alternative with the highest leaving flow or the lowest entering flow is the best.

$$\emptyset^+(a) = \frac{1}{n-1}\sum \pi\,(a,x) \tag{12}$$

$$\emptyset^-(a) = \frac{1}{n-1}\sum \pi\,(x,a) \tag{13}$$

Finally, to apply PROMETHEE II it is necessary to calculate the net flow that allows the ranking of alternatives. The net outranking flow $\emptyset\,(a)$ of each alternative is the subtraction of negative from positive outranking flows (equation 14). At this stage, all the alternatives become comparable because no incomparability remains, and they could thus be ranked by means of complete ranking (PROMETHEE II result). The best alternative is the one having the highest net flow. By finishing the calculations, the obtained fuzzy net flow values could be defuzzified to ease the comparisons.

$$\emptyset\,(a) = \emptyset^+\,(a) - \emptyset^-\,(a) \tag{14}$$

When rather than a decision-maker there are several ones involved, the choice of the preference functions can be global or individual. In the first case, the group decides to adopt the same preference functions. In the second, each of them analyses the problem separately and choose the preference functions which is better suited to his personal points of view. In both cases, individual ranking of alternatives is established by each decision-maker using PROMETHEE II. Then, the different individual rankings are bring together for a global ranking through the PROMETHEE GDSS (standing for Group Decision Support System) in which each individual ranking given by the net flows is considered as a new criterion. The global ranking is obtained by aggregating the individual flows; possibly incorporating the weights allocated to the decision-makers.

3.4.3. Calculation of the overall fuzzy sustainability performance

When using the arithmetic mean method, the fuzzy sustainability performance index (SPI) for each alternative can be computed as in equation 15, where w_n is the fuzzy weight of the criterion and CPI_n is the fuzzy performance value of the alternative with respect to criterion n.

$$SPI = \frac{\sum \boldsymbol{w_n} \otimes \boldsymbol{CPI_n}}{\sum \boldsymbol{w_n}} \tag{15}$$

In the case of applying the F-PROMETHEE method, the obtained fuzzy CPI values are used as the inputs for the decision matrix after normalising all the CPI values in the range from 0 to 1 using equation 16. On the basis of the calculation procedure in stage 2, the spectrum of the CPI values is a symmetrical scale centred on 0. By normalising the CPI values, the evaluation table is more readable and it shows how much each alternative contributes to the criteria. However, normalisation is not required. Afterwards, all the steps of the F-PROMETHEE method are followed to estimate the fuzzy net flows of the alternatives.

$$\boldsymbol{CPI'_n} = \frac{\boldsymbol{CPI_n - minCPI_n}}{\boldsymbol{maxCPI_n - minCPI_n}} \tag{16}$$

where:

CPI'_n is the normalised fuzzy performance value of the alternative with respect to criterion n,

maxCPIn is the maximum value of the upper bound of the fuzzy criteria performance values of all the alternatives and

minCPIn is the minimum value of their lower bound.

3.5. Stage 5: Defuzzification of the fuzzy global performance of the alternatives

Once the fuzzy SPI or fuzzy net flow calculations are complete, the alternatives being studied must be compared for ranking purposes. Defuzzification is applied to convert the obtained fuzzy SPI or fuzzy net flows into appropriate crisp values. In this paper, fuzzy performance value defuzzification will be performed with the COG method, which computes the centre of gravity of the area under the membership function and uses the α-cut approach. The latter compares two fuzzy sets in terms of their α-cuts [81]. This approach allows us to describe the specific levels of confidence associated with the decision environment. The α-cuts of the fuzzy SPI or fuzzy net flows obtained for each of the fixed confidence levels could be compared directly or based on one value: the lower bound, upper bound or mean of the bounds to capture the pessimistic, optimistic or moderate attitude of the decision maker, respectively. When using this approach, the more α-cuts that are analysed, the more reliable the results achieved [82].

3.6. Stage 6: Selection of the most sustainable alternative

The last stage aims at ranking the potential risk management strategies to select the most sustainable one amongst them.

4. An application of the proposed approach

The proposed approach for decision making under uncertainty is put into practice to select the most sustainable strategy amongst three strategies intended to manage flood risks in a city referred to as FloodedCity hereafter located in Meurthe-et-Moselle County, France. With approximately 4,700 inhabitants, the city covers 18 km^2 and is situated along the Moselle. The maximal known flooding is 150-year flooding, with the highest water level near 2.45 m. The city has been affected by some severe floods (in 1947, 1983, and 2006) and thus was chosen as a suitable application site for sustainable flood management decision making.

The strategies that will be evaluated against the status quo have been defined in collaboration with members of the mayor's office. The management strategies were identified relying on a global flood response doctrine, which suggests that all property owners may protect themselves from floods while avoiding making the floods more dangerous to their neighbours. Three management options (**A1, A2** and **A3**) have been developed by relying on two basic ways to cope with floods: "protect people against floods by confining the river to its bed" and "live with floods with adaptative solutions". In addition to the flood response objective, each alternative is associated with new development projects in the flood-prone areas. Indeed, FloodedCity plans to:

- construct housing and commercial infrastructure (elevated on pilings above the known maximal flooding level) mainly in the inner part of a low to moderate hazard prone area of the city with a high urban development potential,
- establishment of economic activity plants, which will not suffer from inundations, are weakly sensitive to them, or have security measures for their sensitive equipment.

Alternative **A1** consists of willingly respecting the regulatory constraints for new buildings in the flood-prone areas. This alternative implies taking the information on the potential risks of flooding into account when planning new buildings (or rehabilitating existing ones) to use construction methods and/or materials that are adapted to the flooding situation and to the level of the hazard. For instance, such construction methods include avoiding cellars and designing building apertures appropriately. The second alternative (**A2**) aims at reinforcing and raising the existing railway embankment along the river so that it can be used as a dyke. This dyke will be dimensioned to protect against the maximal known flooding level, that is, a 150-year event. Finally, **A3** consists of willingly respecting the regulatory constraints for all the existing buildings located in the hazard-prone areas through individual protective equipment that allows the prevention, mitigation, or delay of water entering buildings. In this case, the measures that can be taken by each household to protect assets against damage are water-proof closings for apertures, positioning the heating and electric facilities above the water level, moving furniture to upper floors, etc. These strategies are supposed to have different characteristics while remaining identical in terms of technical complexity during implementation.

4.1. Deterministic assessment of the alternative strategies

The three studied strategies were assessed applying the deterministic methodological framework used by [82]. First, by applying AHP and with a CR of 0.07, the criteria weights are established as follows (in a decreasing order): 0.39 for C2: "*Economic Sustainability*", 0.3 for C1: "*Technical and functional effectiveness*", and 0.15 for C5: "*Institutional sustainability*" whilst C3: "*Social Sustainability*" and C4: "*Environmental sustainability*" have an equal weight of 0.08. For the compensatory perspective, the deterministic global ranking is led by the alternative A2 with a SPI value equals to 1.996, followed by A3 (SPI = - 0.28). The strategy A1 is the less sustainable one with a SPI of - 0.517. The results of PROMETHEE II calculation show that A2 appears as the most sustainable risk management strategy with a net flow value equalling to 1 ($\varnothing^+ = 1$ and $\varnothing^- = 0$). The alternative A3 is obtained as the second option ($\varnothing = -0.37$, $\varnothing^+ = 0.19$ and $\varnothing^- = 0.56$) and A1 as the last one ($\varnothing = -0.63$, $\varnothing^+ = 0.06$ and $\varnothing^- = 0.69$). Clearly, the compensatory and the non-compensatory results are in consensus about selecting A2 as the risk management strategy to be implemented.

4.2. Input data of the fuzzy assessment process

As stated previously, the calculation of the criteria performance levels is not the focus of this paper. Consequently, the input data for this application are the values of the criteria scores extracted from the work of Edjossan-Sossou [83]. The fuzzy CPI values resulting from stage 2 of the methodology are given in Table 3 by using five α-cut levels, with $\alpha = \{0, 0.3, 0.5, 0.7, 1\}$ corresponding to the retained confidence levels $(1 - \alpha)$. These values provide a comprehensive view of the possible confidence levels that a decision maker can express about his decision in an uncertain environment from the most confident to the least. Furthermore, as shown in Table 3, the CPI values of the alternatives are expressed in the form of various membership function shapes (from singleton to polygonal).

It could be seen that there is practically no uncertainty in some of the criteria performance values, such as the score of the criterion C1: "*Technical and functional effectiveness*" for A2, while there is an definite uncertainty in the scores of criterion C3: "*Social sustainability*" for both alternatives. This dataset corresponds to the estimation at only one stage in time, and it must be remembered that sustainability assessment must be addressed as a continuum ranging from the short to long term.

Table 3. Membership functions of the CPI value for each alternative

		Alternatives		
Criteria	**α**	**A1**	**A2**	**A3**
C1: Tech. & Funct. Effectiveness	**1**	[0.22, 0.56]	{2.22}	[0.67, 0.9]
	0.7	[0.22, 0.56]	{2.22}	[0.63, 0.93]
	0.5	[0.22, 0.56]	{2.22}	[0.61, 0.95]
	0.3	[0.22, 0.56]	{2.22}	[0.59, 0.97]
	0	[0.22, 0.56]	{2.22}	[0.56, 1]
C2: Economic Sustainability	**1**	[- 2.47, - 2.36]	[0.64, 0.75]	[- 1.88, - 1.69]
	0.7	[- 2.47, - 2.36]	[0.64, 0.75]	[- 1.95, - 1.66]
	0.5	[- 2.47, - 2.36]	[0.64, 0.75]	[- 1.97, - 1.64]
	0.3	[- 2.47, - 2.36]	[0.64, 0.75]	[- 1.99, - 1.62]
	0	[- 2.47, - 2.36]	[0.64, 0.75]	[- 2.03, - 1.58]
C3: Social Sustainability	**1**	[1.82, 2.79]	[2.79, 3.66]	[- 0.26, 0.39]
	0.7	[0.27, 4.44]	[0.93, 5.88]	[- 2.16, 2.82]
	0.5	[- 0.79, 5.54]	[- 0.34, 7.19]	[- 3.47, 4.43]
	0.3	[- 1.84, 5.88]	[- 1.59, 7.79]	[- 4.74, 5.48]
	0	[- 3.42, 5.88]	[- 3.47, 7.95]	[- 6.08, 5.97]
C4: Environmental Sustainability	**1**	{- 2.18}	{1.74}	[- 2.18, - 1.85]
	0.7	[- 2.22, - 2.15]	[1.7, 1.77]	[- 2.22, - 1.81]
	0.5	[- 2.24, - 2.12]	[1.68, 1.8]	[- 2.24, - 1.79]
	0.3	[- 2.27, - 2.09]	[1.65, 1.83]	[- 2.27, - 1.76]
	0	[- 2.54, - 1.82]	[1.38, 2.1]	[- 2.54, - 1.49]
C5: Institutional Sustainability	**1**	[2.69, 3.25]	[4.57, 4.88]	[2.44, 3]
	0.7	[1.84, 4.15]	[3.39, 5]	[1.67, 3.94]
	0.5	[1.28, 4.25]	[2.59, 5]	[1.16, 4.25]
	0.3	[0.72, 4.25]	[1.81, 5]	[0.64, 4.25]
	0	[- 0.13, 4.25]	[0.63, 5]	[- 0.13, 4.25]

4.3. Criteria weights estimation using the F-AHP

In order to define the weights to be assigned to the criteria, a questionnaire was designed to elicit opinions about the relative importance of the criteria based on the specific sustainable development context of the study area and considering a triangular fuzzy number scale (see Table 1). The questionnaire was completed by a panel of members of the mayor's office (essentially those who are in charge of technical services, territorial development, social well-being, etc.). The obtained pairwise comparisons are tabulated in Table 4. The results of the consistency checking and the weights of each criterion are shown in Table 4.

Table 4. Comparison matrix of the criteria

	C1	**C2**	**C3**	**C4**	**C5**
C1	(1, 1, 1)	(1/4, 1/2, 1)	(3, 5, 7)	(3, 5, 7)	(1, 2, 4)
C2	(1, 2, 4)	(1, 1, 1)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)

C3	(1/7, 1/5, 1/3)	(1/7, 1/5, 1/3)	(1, 1, 1)	(1, 1, 1)	(1/4, 1/2, 1)
C4	(1/7, 1/5, 1/3)	(1/5, 1/3, 1)	(1, 1, 1)	(1, 1, 1)	(1/4, 1/2, 1)
C5	(1/4, 1/2, 1)	(1/5, 1/3, 1)	(1, 2, 4)	(1, 2, 4)	(1, 1, 1)

As CR < 0.1, the degree of inconsistency present in the elicited judgements is acceptable, and the obtained criteria weights are consistent. In the present case, based on the normalised weights (Table 5), criterion C2: "*Economic Sustainability*" has the highest contribution to the final goal of sustainable flood management in the city. It is followed by C1: "*Technical and functional effectiveness", C5*: "*Institutional sustainability*", C4: "*Environmental sustainability*", and C3: "*Social Sustainability*". The ranking resulting from the application of F-AHP is quite the same as those from AHP, except the fact that the fuzzy approach allows discriminate between C3 and C4; the latter being slightly higher than the other. While both appeared equals with the deterministic calculations, C4 has a higher relative weight than C3 with the fuzzy approach. Moreover, the deterministic judgements result in a lower consistency ratio than do the fuzzy ones meaning that the deterministic weights are more consistent, and hence more acceptable.

Table 5. Weights of the criteria

	Fuzzy weights	Defuzzified weights	Normalised weights	
C1	(0.120, 0.305, 0.779)	0.401	0.299	λ_{max} = 5.418 CI = 0.1046 CR = 0.0934
C2	(0.128, 0.394, 1.000)	0.507	0.378	
C3	(0.036, 0.073, 0.175)	0.095	0.071	
C4	(0.038, 0.081, 0.217)	0.112	0.084	
C5	(0.056, 0.148, 0.472)	0.225	0.168	

4.4. Ranking of the management strategies according to their fuzzy performance values

Since the criteria weights are known, the sustainability of each option is calculated using both compensatory (fuzzy arithmetic mean) and non-compensatory (F-PROMETHEE) approaches.

4.4.1. Fuzzy arithmetic mean results

The uncertain estimates of the SPI values for each alternative are illustrated in Figure 5, which shows that A2 is the highest-ranked strategy. This alternative has a discernible advantage over the others. However, alternatives A1 and A3 are not necessarily directly comparable because their SPI distributions partially overlap each other. For example, the most possible performance values (α = 1) can be at least approximately – 0.55 and – 0.37, while at most about – 0.25 and – 0.07 for A1 and A3, respectively. They have the same lower performance value, while A3 has a higher upper performance value than A1. The defuzzified values of the sustainability performance values of each alternative are A1 = – 0.427, A2 = 1.854 and A3 = – 0.216. Depending on these values, the final ranking order of the three alternatives is A2 > A3 > A1, meaning that A2 is suggested as the most sustainable strategy and A1 the least sustainable one.

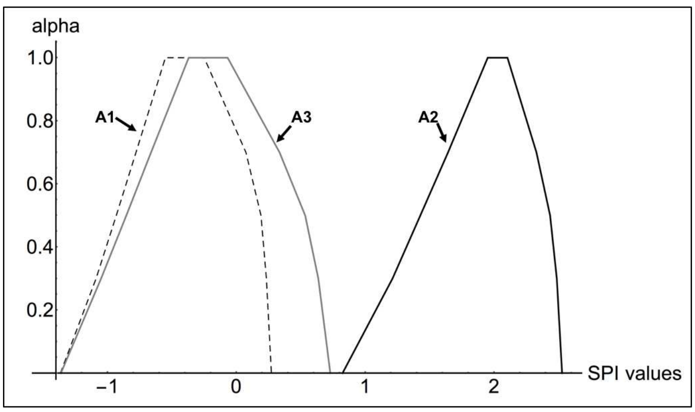

Figure 5. Comparative representation of the sustainability performance index values of the 3 alternatives

We can conclude that the overall decision based on both approaches is to implement the risk management strategy A2 which aims at reinforcing and raising the existing railway embankment along the river so that it can be used as a dyke. Although the ranking is the same as what was found through the calculation of the deterministic SPI values, it could be noted that the performance value of the most sustainable strategy (A2) resulting from the fuzzy approach is lower than the one from the other approach. The opposite pattern is observed for A1 and A3. Yet, we do not have enough information to wisely conclude that an approach overestimate or underestimate the obtained performances. However, one can argue that given all the uncertainties accounted for in the calculations of SPIs, the rational level of the SPIs resulting from fuzzy approach is the higher in comparison with the one of the second group. In the case of A2, for instance, the decision-maker could be more confident with the SPI value of 1.854 than 1.996.

4.4.2. The F-PROMETHEE results

Table 6 exhibits the preference matrix obtained from the fuzzy CPI (see Table 3) using the usual preference function as well as the aggregated preference functions to represent how one alternative is preferable to another. For the sake of simplicity, this table presents only the results corresponding to the minimum and maximum values for the core and support of the membership functions. For example, when focusing on the most possible values (α = 1) and in the context of a pessimistic attitude (see the shaded cells), A1 is strictly preferable to A3 only on criterion C3, A3 is preferable to A1 on criteria C1 and C2, while A2 is preferable to the two other alternatives considering all five criteria (except in the case of criterion C3, for which there is not a strict preference between A1 and A2).

Table 6. Preference functions for the pairs of alternatives

			C1	**C2**	**C3**	**C4**	**C5**	**π (a, b)**
Lower value α = 0	**A1**	**A2**	0	0	0	0	0	0
		A3	0	0	0	0	0	0
	A2	**A1**	1	1	0	1	0	0.286
		A3	1	1	0	1	0	0.286
	A3	**A1**	0	1	0	0	0	0.128
		A2	0	0	0	0	0	0
Upper value α = 0	**A1**	**A2**	0	0	1	0	1	0.647
		A3	0	0	1	1	1	0.864
	A2	**A1**	1	1	1	1	1	2.643
		A3	1	1	1	1	1	2.643
	A3	**A1**	1	1	1	1	1	2.643
		A2	0	0	1	0	1	0.647
Lower value α = 1	**A1**	**A2**	0	0	0	0	0	0
		A3	0	0	1	0	0	0.073
	A2	**A1**	1	1	0	1	1	0.928
		A3	1	1	1	1	1	1
	A3	**A1**	1	1	0	0	0	0.699
		A2	0	0	0	0	0	0
Upper value α = 1	**A1**	**A2**	0	0	0	0	0	0
		A3	0	0	1	0	1	0.221
	A2	**A1**	1	1	1	1	1	1
		A3	1	1	1	1	1	1
	A3	**A1**	1	1	0	1	1	0.928
		A2	0	0	0	0	0	0

Figure 6 presents the membership functions of the leaving, entering and net flows. The three comparative representations show that the membership functions of the fuzzy flows noticeably overlap each other, making a direct comparison difficult. Focusing on the most possible values, A2 has the lowest entering flow and the highest leaving flow, while A1 has the highest entering flow and the lowest leaving flow. The defuzzified values of the outranking flows are provided in Table 7. The flood management options are ranked in ascending order based on the obtained defuzzified values of the net flows. The resulting PROMETHEE II ranking order is A2 > A3 > A1 (where ">" indicates "is more sustainable than"). Thus, A2 is identified as the most sustainable strategy (with scores of 1.02, 1.26 and 0.24 for Ø, Ø+ and Ø–, respectively), and A1 is the least sustainable strategy. This conclusion is similar to that obtained with the fuzzy arithmetic mean.

Table 7. The defuzzified outranking flows

Alternatives	Ø+	Ø-	Ø	Rank
A1	0.28	1.23	- 0.95	**3rd**
A2	1.26	0.24	1.02	**1st**
A3	0.73	0.80	- 0.07	**2nd**

As a reminder, a typical preference function was considered for all the criteria when performing the F-PROMETEE ranking. This preference function, contrary to the other shapes, does not include any threshold values. The dominance relation between two options is quite strict on the preference of the decision maker; incomparability cannot hold for pairwise comparisons. A perspective could be gained by testing the robustness of the obtained ranking to changes in the choice of the preference function as well as investigating the effect of the preference value uncertainty on the ranking.

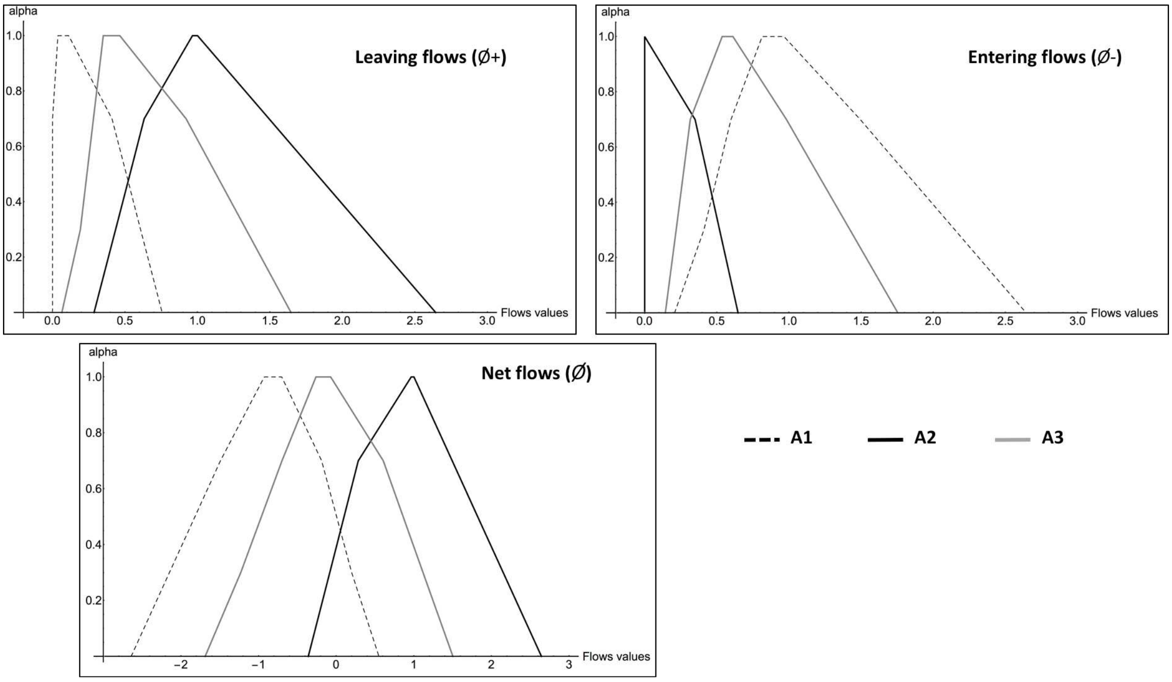

Figure 6. Comparative representations of the leaving, entering and net flows

4.4.3. Sensitivity analysis

After obtaining the fuzzy SPI values or net flows, the decision maker must select an α level to obtain an interval of values. The crisp value should be selected from this interval based on the pessimistic or the optimistic attitude of the decision maker. For example, a decision maker may wish to establish the final alternative ranking based on the net flows obtained from an α value of 0.3. The intervals of the outputs will be [- 2.150, 0.198], [- 0.084, 2.150] and [- 1.231, 1.117] for A1, A2 and A3, respectively. Applying an α-cut analysis, a sensitivity analysis is performed at the five confidence level values which considers the three decision makers' attitudes for the fuzzy SPI. The results are presented in Figure 7. From this figure, it can be observed that the results are consistent enough to show that A2 has the highest performance at all the confidence levels and types of attitude followed by A3 and A1, respectively. The same analysis is performed for the fuzzy net flows to check their sensitivity to the confidence levels and the decision maker's attitude. The results indicate that the rankings are also consistent at the different α levels for a pessimistic, moderate and optimistic decision maker.

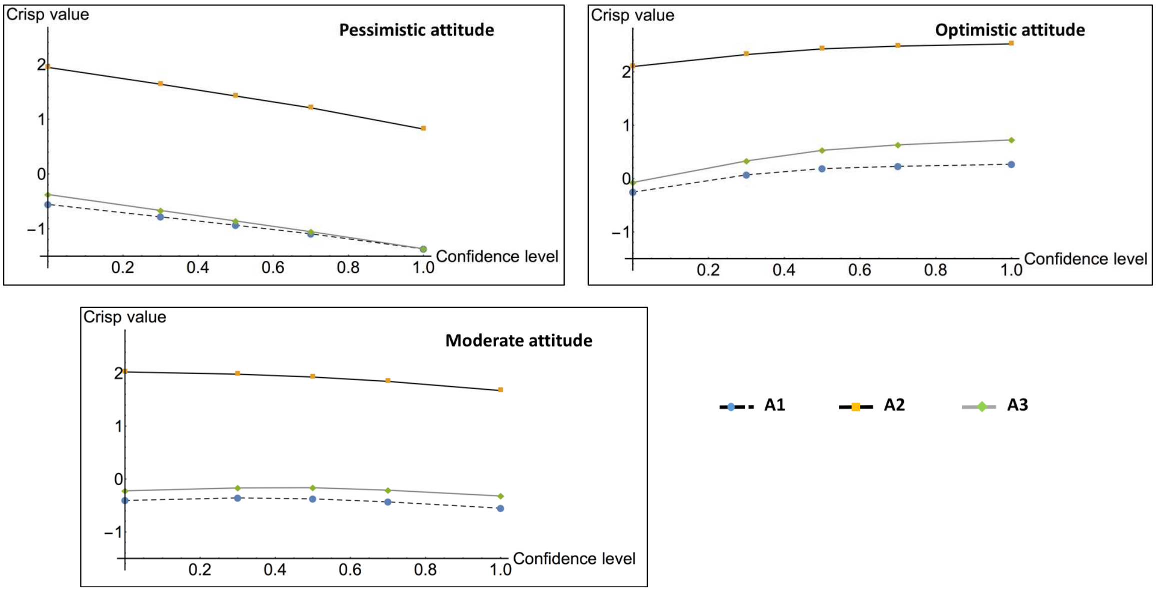

Figure 7. Sensitivity analysis of the fuzzy arithmetic mean ranking

4.4.4. Discussion

This application was studied to illustrate the methodological approach. The first objective was to analyse the influence of uncertainty on the decision-making by comparing deterministic and fuzzy results. However, with the present case study and given the fact that the results are quite the same, it is not possible to conclude on this influence (no real variability was found).

The second objective is to raise the awareness of the decision-makers on the fact that in the real world the results are not necessarily unique crisp values but could be in the form of intervals leading sometimes to overlapping; so that two options which look clearly different with crisp calculations may turn concurrent when shifting to fuzzy approach. This case study has shown how data-induced uncertainty can affect the sustainability performance of risk management strategies and consequently, management decision-making. Figures 5 and 6 show that the resulting membership functions of the sustainability assessment process may partially or completely overlap each other. A certain compliance of the strategies exists within their common areas. If two membership functions overlap each other, the larger the common area is, the higher the compliance degree. This issue can have the potential to lead to the incomparability of the strategies or decrease the decision maker's confidence about ranking one over the others. For example, the supports of the fuzzy net flows (Figure 6) overlap from – 0.361 to 0.549, indicating that in this range, the three alternatives can objectively perform similarly or A1, which is ranked as the least attractive solution, can record a better score than the two other alternatives.

A graphical representation can allow a broad understanding of the fuzzy results and support decision makers to easily grasp the confidence level at which there exists a clear difference between the results (no more overlapping) considering the uncertainty in the input data. For instance, when comparing the SPI values (Figure 5), it is clear that the risk level is nearly nil to say that A2 is the best alternative, and there exists uncertainty about ranking A1 and A3 for all the possible confidence levels as their membership functions overlap each other from the cores to the supports. The confidence level to conclude that A2 has better net flows (Figure 6) than A1 and A3 is approximately 55 % and 23 %, which correspond to α = 0.45 and α = 0.77, respectively (whilst A3 has better net flows than A1 when α = 0.86).

The visualization of the results can thus play an important role in improving the awareness and understanding of uncertainty and variability in the results.

Sometimes, due to overlapping, reliable conclusions cannot be made based on the fuzzy scores as such. Thus, the F-MCDM approaches require a defuzzification procedure to convert the fuzzy scores to crisp scores. There are different defuzzification procedures; however, they can provide different rankings. In this case study, the intuitive rankings shown by the position of the membership functions are validated by the rankings based on the COG defuzzification method and α-cuts analysis. Indeed, the results of the sensitivity analysis show that using the COG defuzzification method or applying an α-cuts analysis does not affect the obtained ranking order. In addition, an α-cuts analysis allows the rating from a pessimistic scenario to an optimistic scenario. Although Figure 7 clearly shows that A2 is the most sustainable flood management strategy under any degree of confidence of the decision maker with various attitudes towards risk, it can be seen that when the decision makers tend to favour pessimistic scenarios and adopt the maximum degree of confidence, A1 and A3 may be considered incomparable strategies. It can be settled that the rankings based on an α-cuts analysis may depend on the scenario that best fits the risk attitude adopted by the decision maker. Therefore, the retained scenario must be specified (pessimistic, moderate or optimistic) when making a final decision to justify the choices and avoid biases.

Both the fuzzy arithmetic mean and F-PROMETHEE methods deliver similar ranking orders (keeping in mind that a limitation of this study could be the choice of the usual preference function for the pairwise comparison of options when using the F-PROMETHEE method). This indicates that, in the context of the present case, the two aggregation approaches (compensatory and non-compensatory) lead to the same result. This does not mean that one specific method is better than the other and that both the fuzzy arithmetic mean and F-PROMETHEE methods seem to be appropriate for the selection of the most sustainable natural risk management strategy. Consequently, the selection of one of these methods depends on the specificities of the circumstances at hand. It is a crucial issue in MCDM to determine whether the final ranking is dependent and or sensitive to the approach adopted for aggregating the criteria scores. The aim of this case study was not to make a comparison between the fuzzy arithmetic mean and F-PROMETHEE methods but to highlight the ability of the suggested methodology to allow both aggregation approaches. To deeply study a comparison between the results of these ranking methods, more case studies need to be conducted.

This illustrative case shows the originality and contribution of the proposed approach to effective decision-making under uncertainty. Although this approach allows us to consider data-induced uncertainty for both the quantitative and qualitative data, and it also allows the decision maker makers to define various confidence levels associated with their results/decisions, indicating that the latter may present differences depending on how membership functions overlap. By all means, this approach could further help evaluate the sustainability of natural risk management strategies, prioritize alternative strategies for the successful implementation of sustainable risk management, handle data-induced uncertainty in the sustainability assessment process and improve the reliability of sustainable risk management decisions made under uncertainty in the input data.

5. Conclusion

Currently, the selection of the most sustainable strategy or policy is of prime concern to achieve disaster risk reduction. In addition, taking uncertainty into account has become a common practice in many decision-making processes, and an estimation of uncertainty must always be considered when performing sustainability assessment as a support tool for decision making. Sustainable natural risk management decision making generally involves various types of objectives and issues as well as information that could be tangible and/or intangible. The potential consequences of alternative risk management strategies may be difficult to predict accurately; these predictions and, subsequently, the resulting sustainability assessment may include uncertainty. However, considering uncertainty within the sustainability assessment process is still rare. Therefore, the purpose of this study was to provide an operational approach for selecting the best strategy or policy to meet the sustainability criteria under data-induced uncertainty. Consequently, capturing the uncertainty of the results may lead to improved reliability.

This paper introduced a decision-making process based on a fuzzy framework that allows handling data uncertainty to capture the uncertainty or fuzziness that exists in sustainability assessment outcomes. The presented methodological approach is not a newly designed method for handling MCDM problems but it is a formalized approach to guide decision-makers through the sustainability assessment of risk management strategies under uncertainty (which could be on the input data, the criteria weights and the aggregation option) in order to inform them about the potential influence of uncertainty on the obtained outcomes. It is an integrated approach that combines the fuzzy AHP, fuzzy arithmetic mean and fuzzy PROMETHEE methods. By using the F-AHP, the decision maker can effectively represent the uncertainty in the pairwise comparisons of the criteria for their weight derivation. Within this approach, the fuzzy arithmetic mean and F-PROMETHEE methods were suggested as optional methods to determine the alternative rankings depending on the preferred aggregation approach, thus strengthening the approach and making it more versatile and accommodating to different visions of sustainability.

The proposed methodology was applied to a practical flood management case as an illustrative study to demonstrate its applicability. The findings of this study provide valuable insights regarding handling uncertainty during the sustainability assessment process. The results analysis highlighted that the rankings may depend on the criteria aggregation approach, the confidence level chosen by the decision makers, and their attitude. In summary, the proposed approach provided a good approach to consider data uncertainty in a sustainability assessment process and analyse how this uncertainty affects the assessment results. It was also shown to be an appropriate and practical methodological basis that can be used by natural risk managers to select the most suitable strategy to implement to ensure the sustainable management of these risks when making decisions in uncertain environments.

The main advantages of the methodology are the following. It allows the use of quantitative data together with qualitative data and considers uncertainty in both types of data (represented in the form of sets/intervals of values associated with the given levels of confidence and fuzzy numbers, respectively). It is flexible in that it incorporates both compensatory (via fuzzy arithmetic mean method) and non-compensatory (via fuzzy PROMETHEE method) points of view regarding the aggregation of the sustainability criteria. These two methods were chosen based on their popularity. For further studies, other F-MCDM methods could be used. It has flexibility in that, on the one hand, it can be applied regardless of the shape of the membership functions (thanks to the use of interval arithmetic with α-cuts), and it allows using crisp values instead of uncertain values whenever decision makers decide to do so. On the other hand, two different defuzzification methods (the COG and α-cuts methods) can be used to convert the fuzzy results into crisp values for the final ranking.

Although the proposed methodology is quite reliable for ranking alternative strategies, it also has some limitations. One of them is that the use of fuzzy sets induces a calculation effort higher than that in a deterministic calculation process. Particular attention should be paid to reducing the calculation costs by developing mathematical models for the automatic computation of the outputs of the framework. Another limitation lies in the fact that the resulting fuzzy sustainability performance values may have wide ranges due to consecutive interval arithmetic operations, as well as from an overestimation of the uncertainty associated with the sustainability performance values. Future research could be targeted to investigate the impact of such overestimation on decisions. Despite its limitations, this approach can be applied effectively to support any sustainable managerial decision-making within uncertain environments.

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