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Assessing Climate Transition Risks in the Colombian Processed Food Sector: A Fuzzy Logic and Multi-Criteria Decision-Making Approach

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Abstract: Climate risk assessment is critical for organisations, especially in sectors such as the processed food sector in Colombia. This study addresses the identification and assessment of the main climate transition risks using an approach that combines fuzzy logic with several multi-criteria decision-making methods. This approach makes it possible to handle the inherent imprecision of these risks and to use linguistic expressions to better describe them. The results indicate that the most critical risks are price volatility and availability of raw materials, the shift towards less carbon-intensive production models, increased carbon taxes, technological advances, and associated development or implementation costs. These risks are the most significant for the organisation studied and underline the need for investments to meet regulatory requirements, which are the main financial drivers for organisations. This analysis highlights the importance of a robust framework to anticipate and mitigate the impacts of the climate transition.

Keywords: climate transition risk; risk matrix; risk assessment; fuzzy logic; multi-criteria decision making

MSC: 26A15; 26D15; 41A17; 41A25; 41A35

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1. Introduction

Climate-related risks have wide-reaching implications, causing economic, material, environmental, and social damage. To mitigate these losses, data-driven models that analyse historical data are emerging, helping to improve the assessment of these risks and achieve a more accurate and comprehensive understanding of the potential impacts associated with climate-related hazards [1]. By leveraging the insights gained from the analysis of historical data, companies aim to improve the ability to anticipate, prepare for, and respond to the challenges posed by climate-related risks. There are several methods to assess climate risk and make decisions accordingly, and the most appropriate approach greatly depends on factors such as data requirements, time frame, and organisational purpose [2].

Increasingly severe weather conditions pose growing systemic risks to businesses in the global economy [3], with climate change impacting natural ecosystems through rising sea levels, increased average temperatures, changes in precipitation patterns, and temperature fluctuations. These physical effects generate significant risks for companies, commonly referred to as climate physical risks, which can lead to financial losses due to asset damage or business interruptions [4]. In response to the recognition of these risks, regulatory measures are being implemented to address the impacts of climate change. This has led to an increase in climate regulations that impose financial risks on organisations, often resulting in additional operating and investment costs. Moreover, climate transition risks, which are associated with the process of adapting to a low-carbon economy, also arise. These risks can be classified into four categories: regulatory risks, which encompass changes aimed at mitigating climate change and promoting decarbonisation; technological risks, related to the shift from greenhouse gas (GHG)-generating technologies to cleaner alternatives; market risks, which involve shifts in supply and demand dynamics driven by new production and consumption patterns focused on GHG reduction; and reputational risks, stemming from changes in stakeholder perceptions of a company's contribution to a low-carbon economy [4].

In essence, both climate physical and transition risks are intertwined, as the physical impacts of climate change and the necessity to transition towards a sustainable economy present various challenges to businesses. The combined effect of these risks underscores the importance of understanding and managing the regulatory, technological, market, and reputational risks that arise as organisations navigate the transition to a low-carbon future.

The correlation between physical risk and transition risk is clear: as transition policies are implemented, the impact of physical risks is generally mitigated. Furthermore, when physical risks are more likely to manifest, the need for effective transition measures increases [5].

Climate change has become one of the most pressing global issues. It is essential to analyse the science of climate change and the uncertainties associated with it, as well as to identify and explain the associated climate change risks and the financial implications [5].

Predicting the future has always been a human desire, but when it comes to climate change, its impacts, mitigation, and adaptation, there is a great deal of uncertainty. Scientists have estimated the probability of different outcomes for greenhouse gas emissions (GHG) and temperatures, but this still carries some risk.

The exact nature, timing, frequency, intensity, and location of the effects of climate change cannot be predicted due to the uncertainties involved. These uncertainties are based on a variety of demographic and socioeconomic elements, such as technology, values and preferences, and policies [6]. In addition, our limited understanding of the climate system leads to scientific uncertainty [7].

Companies must recognise, quantify, monitor, control, and communicate their exposure and vulnerability to these risks to their stakeholders. Companies must demonstrate how they are mitigating significant risks and have in place reliable policies or regulations to manage these risks.

In this situation, according to [8] a successful risk management system should have three goals: first, to identify the main sources of climate risk and how it is spread; second, to map and assess climate-related exposure and any areas of risk concentration; and third, to create financial risk metrics for climate risks. In this investigation, we address the first two points; the third point will be addressed in future research.

However, a primary task is the timely identification of climate risks for an organisation. This is articulated with the most recent regulation implemented in Colombia, the External Circular 031 of the Superintendencia Financiera (SFC), Colombia's financial regulator, which requires companies that are listed to identify the risks related to climate change to which they are exposed and to disclose them to their stakeholders.

To address this complexity, a comprehensive and integrative model is needed to weigh these factors in an interconnected way. Multi-criteria decision making (MCDM) methods provide a structured and analytical approach to this problem, allowing for the consideration of multiple variables and the evaluation of various scenarios that could affect an organisation's risk profile. MCDM thus offers a more informed and strategic decision-making framework in the ever-changing climate context.

Companies often turn to risk matrices to make decisions, which are intended to assess the probability and effect of different risks. However, traditional approaches are inadequate to accurately model certain climate risks due to their unpredictable and ever-changing nature [6]. To address this, tools that are not only easy to update but also promote effective communication within the organisation are needed. Here, fuzzy logic (FL) can be beneficial. FL enables the consideration of multiple factors and relationships in a flexible manner and is capable of dealing with the uncertainty associated with risk assessment. Furthermore, it is well suited to the need for adaptability and communication effectiveness, making it a powerful tool for risk assessment in the unpredictable climate environment.

Therefore, this research focuses on identifying and measuring the risks of climate transition that can affect a company in the processed food sector in Colombia; this is achieved by building a risk matrix where the probability of occurrence and impact are evaluated and analysed from a financial perspective in the organisation, as well as the level of risk exposure, using computational techniques and expert judgement. To achieve this objective, 10 MCDM methods and the FL approach are compared, and the one that best fits the analysed problem is selected. We selected a fuzzy method because FL can work with uncertainty and imprecision and solve problems where there are no defined limits or precise values [9]. This situation occurs in the concept of a risk assessment matrix, due to the uncertainty of climate change.

In this context, we introduce a comprehensive system for identifying and addressing climate transition risks, with the aim of mitigating their potentially disruptive effects on business. Our system's main objective is to provide organisations with a robust framework that streamlines the identification and assessment of these risks and enables them to proactively implement measures that effectively minimise their impact. For organisations, identifying and assessing climate-related risks constitutes a multifaceted challenge due to their heterogeneous nature. Unlike conventional methods, our approach employs fuzzy logic to handle the ambiguity of these risks and contrasts them with various multi-criteria decision-making techniques in the literature. This novel method enables the use of linguistic terms for risk analysis, offering a more accurate description of risks and their impacts. We find that critical risks for this organisation include price volatility, raw material availability, the transition to less carbon-intensive patterns, higher carbon taxes, technological advances, and development or implementation costs. This highlights the need for investments to meet regulatory requirements, which are the primary financial motivators for organisations. Our research identifies key risks and provides a comprehensive classification and quantitative analysis using fuzzy logic, marking significant progress in the field.

The novelty of the paper lies in the integration of the TOPSIS method with a fuzzy logic system for transitional climate risk assessment. Unlike previous approaches that use TOPSIS up to the weighted normalised matrix, and then, calculate distances to ideal solutions, this study applies fuzzy logic to create an expert rule-based risk matrix after obtaining the weights with TOPSIS. This hybrid approach (TOPSIS-Fuzzy) allows for managing uncertainty and imprecision in risk assessment, providing a more accurate and contextualised representation of climate risks for organisations, especially in the processed food sector in Colombia.

The remainder of this article is structured as follows:

- Section 2 reviews and comments on relevant studies in the literature;
- Section 3 describes the data and the methods employed in this research and provides some background information to better understand and motivate our research approach;
- Section 4 presents the proposed fuzzy system;
- Section 5 presents and comments on the obtained results;
- Section 6 draws the conclusions of this study.

2. Literature Review

2.1. Fuzzy Systems in the Risk Assessment Domain

Fuzzy logic (FL) is a widely used paradigm for modelling and assessing risks in various domains [10,11]. While modern artificial intelligence (AI) methods such as convolutional neural networks and decision-making frameworks are gaining popularity for risk assessment, see, e.g., [12], FL still holds a crucial role in modelling risk variables and their probabilities. As a result, there are numerous studies in the current literature that combine FL with AI techniques. The most effective hybrid systems can be categorised into four groups:

1. FL combined with multi-criteria decision-making methods (MCDMs);
2. FL and neural networks;
3. FL and Bayesian networks (BNs);
4. FL integrated with quantitative risk assessment (QRA).

Each category has its own advantages and disadvantages that make it more appropriate for specific contexts.

Due to their flexibility, MCDM methods have been widely used in conjunction with fuzzy logic, especially in risk management. These approaches provide decision-makers with the means to overcome the limitations of conventional risk prioritisation methods, making them valuable tools in the field [13]. The relevant work is given in [14,15]. These use the "analytical hierarchy process" method to define the mutual impact of partial indicators (occurrence, severity, and detectability) on the risk. To enhance the accuracy of the results, the fuzzy model incorporates the Technique of Preference Order in Similarity to the Ideal Solution (TOPSIS), which helps minimise the dispersion of the results. By extending this approach to fuzzy sets, the model further improves the accuracy and reliability of the results. An interesting review of the literature focused on the application of TOPSIS for provider selection is presented in [16]. In this study, three experts evaluated five alternative TOPSIS-based systems using fuzzy logic linguistic expressions. Similarly, the study in [17] uses a fuzzy decision matrix to assess options based on expert ratings based on various criteria, using TOPSIS as the MCDM method. Failure Modes and Effects Analysis (FMEA) [13] is another commonly used MCDM method for risk analysis. However, it is important to note that FMEA has certain limitations. For example, it can produce the same level of risk for different combinations of risk variable scores, which can lead to misleading results in practical risk analysis. Furthermore, FMEA assigns equal weights to each risk parameter, which can be a disadvantage when determining the criteria weights. To address these limitations, researchers have integrated fuzzy logic and TOPSIS with the classical FMEA method to provide a more comprehensive and effective approach to risk assessment.

In the field of risk management within healthcare organisations, the work in [18] highlights the implementation of a decision support system (DSS) that integrates fuzzy logic theory with Failure Mode and Effects Analysis (FMEA). The proposed methodology, referred to as fuzzy FMEA, addresses the limitations of traditional FMEA by providing fuzzy values for the risk priority number (RPN). This approach is complemented by advanced techniques such as artificial neural networks for risk tolerance classification and support vector machines for prioritising intolerable risks. The developed DSS demonstrated high effectiveness, achieving over 98% accuracy in risk tolerance classification and 74% in prioritising intolerable risks. However, there remains a need to extend the study to other healthcare departments to validate the system's applicability and efficiency across different contexts. On the other hand, risk management in supply chains requires a robust methodology capable of handling uncertainty and imprecise information. To this end, the study in [19] proposes a hybrid model based on the intuitionistic fuzzy set (IF) and the TOPSIS technique. This model, applied in a steel plant, significantly enhances risk management by prioritising critical supply chain factors. The fuzzy methodology enables an efficient representation of uncertain information, improving the quality of supply chain control and offering a more accurate alternative to the traditional RPN system. In the dynamic environment of business operations, risk prevention is a crucial measure. The work done in [20] introduces a Fuzzy Optimisation Membership Estimation (FOME) model, based on Choquet expectation theory, to evaluate and optimise risk prevention systems. The FOME model is implemented using the CICIDS dataset for cyber attack analysis, achieving 99.89% accuracy in attack detection. The proposed approach combines fuzzy logic and optimisation to manage uncertainty and provide a robust solution for risk management in critical organisational environments.

In the context of corporate sustainability, managing risks related to Environmental, Social, and Governance (ESG) aspects is essential. For example, the work in [21] employs the VIKOR method, a multi-criteria technique, to prioritise organisational risks with a focus on sustainability. The methodology includes the evaluation of sub-risks in categories such as geopolitical, economic, social, technological, and environmental risks, based on the analysis of global reports and the participation of experts from various sectors. The results from the VIKOR method enable a ranking of risks that facilitates strategic decision making and enhances the alignment of organisations with sustainable practices. On the other hand, in Yemen's banking sector, managing information security risks is crucial for maintaining operational resilience. The authors of [22] applied an integrated Criterion Impact Loss (CILOS)-TOPSIS model to assess and improve ISRM practices in Yemeni banks. The model helps identify and prioritise key factors in security risk management, such as the existence of a comprehensive business continuity plan and the frequency of data backups. The application of this approach provides a robust framework to guide decision making and effectively allocate resources in managing information security risks.

Neurofuzzy logic systems have shown promise in improving the decision-making process and generating meaningful risk classifications [23]. For example, in a study conducted in [24], a five-layer adaptive neurofuzzy inference system (ANFIS) with two input variables is used to predict wind power and its variability under future climate change scenarios in the northern Caspian Sea. The system employs four Gaussian membership functions for data processing in the first stage with good classification results. Similarly, studies in [25,26] apply multiple ANFIS systems to predict drought and estimate a quantitative measure of drought in the form of the standardised precipitation index on time scales from 1 to 12 months. The results are satisfactory and show high accuracy in the prediction of drought.

The combination of FL and BN has been explored in research studies such as [27,28] to address the limitations of risk assessment, as BNs offer a compact representation of joint probability distributions, while FL provides a means of handling vagueness and ambiguity in probabilistic risk assessment. The assignment of appropriate probabilities to the nodes in the BN architecture is crucial to obtaining meaningful results. By incorporating fuzzy sets, the fuzzy Bayesian network (FBN) approach enables the modelling and management of uncertainty by utilising linguistic values in the decision-making process. An FBN is particularly useful when there is little or insufficient data to determine the probability values of the nodes in the network.

Finally, in the domain of quantitative risk assessment (QRA), a combination of fuzzy logic and quantitative methods has been explored. For example, in the context of the oil industry, the study in [29] proposed a fuzzy QRA approach based on fuzzy logic. This approach allows for the analysis, evaluation, and mitigation of key risks associated with the industry. The models developed in this study consider factors such as frequency and severity of consequences, as well as the level of individual and social risk. The authors used a multistep methodology that included the calculation of the fuzzy frequency of consequences and the individual risk associated with each variable.

These risk assessment systems have been used in several application domains, such as construction [30–32], the mining industry [23,33,34], the health sector [35], the manufacturing sector [36–39], and climate physical risks [25,26,40–42]. However, currently there is no significant study using these approaches in the context of transition risks associated with climate change.

2.2. Multi-Criteria Decision-Making (MCDM) Methods

The purpose of MCDM methods is to generate a ranking of alternatives or variables considering the evaluation of multiple criteria simultaneously. However, decision making becomes complex when there are several criteria, so various methods have been developed to facilitate this process [43]. These methods have been widely studied and have been applied to various problems to facilitate decision making.

When analysing a specific problem, there is no standard process for selecting a method and employing it for the solution. This dilemma has been discussed in the literature because, depending on the applied MCDM method, the results may be different [44]. For the above reasons, we will present in general terms several methods widely used by experts, and then, compare the results in constructing a climate transition risk ranking.

TOPSIS is a method that finds the best alternatives by measuring the distance between the chosen alternatives and the ideal solutions (the ideal solution refers to the phenomenon being evaluated). It is based on the concept that the chosen alternatives should have the shortest distance from the positive ideal solution and the longest distance from the negative ideal solution. This means that the best alternatives are those that are closest to the positive ideal solution and farthest from the negative ideal solution [45].

The COPRAS method was developed in 1996 by Zavadskas and Kaklauskas [46]. Like TOPSIS, this method selects the most appropriate alternative considering the best and worst ideal solutions [47].

The BORDA counting method was developed by Jean-Charles de Borda in 1784. It is a procedure that aims to classify the alternatives according to the sum of the individual preferences of the decision-makers. This is a data aggregation technique that reduces two or more classification formats to a more rational one. The method is quite easy to apply [48].

The simple additive weighting (SAW) method is one of the most widely used additive weighting methods for aggregating a decision-maker's preferences defined by multiple criteria. In this technique, the criteria are mutually independent. Preferences are based on the performance score of an alternative for each criterion, which is weighted by the weight of the respective criterion. The decision-maker defines the weight of the criterion. The overall evaluation score of an alternative is calculated by summing the weighted score of that alternative according to several criteria [49].

The ELECTRE method involves a comparison of alternatives based on how their evaluations and preference weights correspond to the pairwise dominance between them. It looks at both the agreement between the preference weights and the dominance relationships, as well as the difference between the weighted scores. This process is known as "concordance and discordance" and is also known as concordance analysis [50]. The concordance and discordance measure the satisfaction and dissatisfaction from the decision-maker's perspective. The threshold concept is then used to create a core of preferred alternatives [51]. Thus, ELECTRE is an "outranking" method.

The VIKOR technique was developed by Serafim Opricovic to solve decision-making issues with conflicting and incommensurable criteria, with the understanding that compromise is an acceptable way to resolve conflicts. This approach focuses on ranking and selecting from a group of options and determines the compromise solution that is closest to the optimal solution [50].

In 2020, Stevic introduced the MARCOS method for supplier selection in the healthcare industry. This method takes a novel approach to problem solving by considering both anti-ideal and ideal solutions in the early stages. It also proposes a new way of calculating utility functions and combining them. This should help to ensure stability when dealing with a large number of alternatives and criteria [52].

The PROMETHEE approach is used for top-level ranking. This method uses a function that reflects the degree of benefit of one option over another, as well as the degree of disadvantage. PROMETHEE involves a mutual comparison of each pair of alternatives with respect to the given criteria. PROMETHEE I is designed to generate a partial ranking. Partial rankings concentrate on the best choice, not on a full ranking. The PROMETHEE II method produces a full ranking, from the best to the worst alternative [53].

The weighted sum method is a popular choice among WSM techniques, as it is easy to use and follows a logical process. The basic assumption of WSM is that the attributes are independent of each other, which means that the contribution of each attribute to the overall score is not affected by the values of the other attributes [51].

Finally, the CODAS method was first proposed by Ghorabaee et al. 2016, this decision-making technique uses two distance measures, the Euclidean distance and the Hamming distance, to assess the desirability of alternatives by measuring the distance from the ideal negative solution [54].

Table 1 summarises the main characteristics of the MCDM methods analysed.

Table 1. MCDM methods.

Method	Name	Characteristics
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution	Compares options with ideal and anti-ideal solutions
COPRAS	Complex Proportional Assessment	Evaluates alternatives according to benefits and costs
BORDA	Borda Count Method	Ranks options by summation of items in ordered lists
SAW	Simple Additive Weighting	Weighted sum of normalised values
ELECTRE	Élimination et Choix Traduisant la Realité	Uses trade-off relations to rank alternatives
VIKOR	Vice Kriterijumsa Optimizacija I Kompromisno Resenje	Balances conflicting criteria by means of compromise solution
MARCOS	Measurement Alternatives and Ranking According to the Compromise Solution	Evaluates alternatives according to distances to compromise solutions
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluations	Based on preferences and positive and negative flows
WSM	Weighted Sum Model	Weighted sum of decision criteria
CODAS	Combinative Distance-Based Assessment	Uses Euclidean and Manhattan distances to evaluate options

The research gap lies in the lack of comprehensive methodologies to assess transitional climate risks; there are several defined for other types of risks, but none specifically for transitional climate risks. Our innovation is the novel application of an MCDM model (comparing several of the most widely used in the literature, including fuzzy-MCM, and obtaining TOPSIS as the one that gives the most consistent results) to derive criteria weights, followed by a fuzzy rule-based system for the final development of a climate risk matrix for the organisation, taking advantage of expert knowledge to address the uncertainties inherent in risk assessment. This methodological advancement allows for a more accurate and context-specific risk assessment.

3. Materials and Methods

In the field of organisational risk management, the first step involves assessing the potential risk of sources. In the specific context of climate transition risks, this process consists of first identifying the different risks, and then, prioritising them. The latter activity is particularly important because it allows the organisation to lay a foundation to understand potential challenges, gain valuable information about various sources and levels of risk associated with climate change, make more effective decisions, and allocate resources to mitigation and adaptation strategies.

In this study, we identified several risks by reviewing the literature on the most important risks for organisations in the processed food sector in Colombia. To validate our findings, we used expert judgement from an organisation in this sector, which allowed better assessment and understanding of the variables selected previously.

Group decision making can significantly reduce the uncertainty of individual opinions by incorporating diverse perspectives and knowledge, thus minimising cognitive biases. In our study, decision-makers include industry experts and academic researchers, all with extensive experience and knowledge of climate transition risks in the Colombian processed food sector. This ensures a comprehensive and informed decision-making process.

3.1. Risk Matrix Construction

An example of a risk matrix is shown in Figure 1. This visual representation allows for a rapid assessment of risks by providing an intuitive way to gauge their likelihood and the resulting impact with the naked eye. It is important that the risk matrix shows the organisation's appetite for climate change risk. It is also easy to create and read even without in-depth technical or domain expertise. For these reasons, the risk matrix is a popular and widely used tool in organisations to determine which risks are more important and require more attention. Note that this method is based on a subjective definition of risk that combines the severity of the consequences and the expected frequency of the event [55].

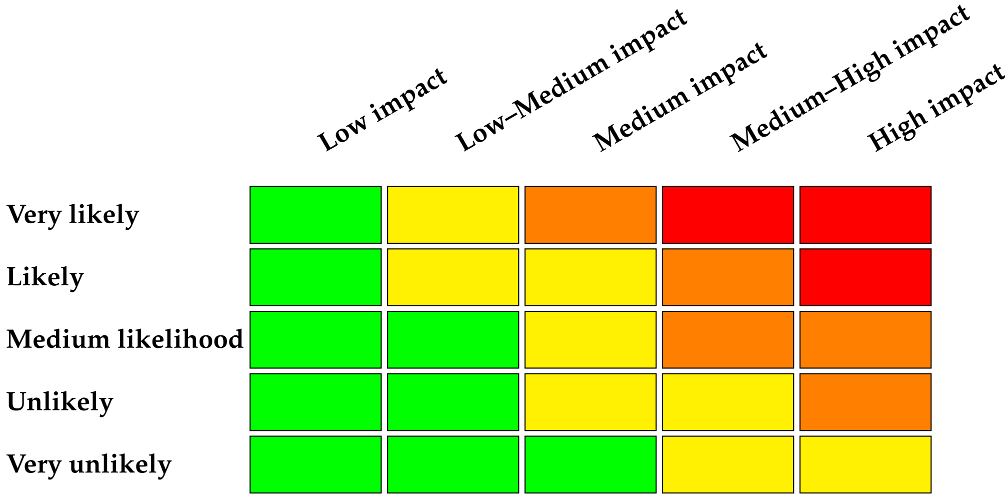


Figure 1. Risk matrix example. Green is used to indicate low risk, yellow to indicate medium risk, orange to indicate high risk, and red to indicate critical risk.

The development of the risk matrix was executed in multiple phases. Initially, risk variables were identified and chosen through an extensive literature review and expert consultations. Subsequently, probability and impact scores were allocated to each risk using fuzzy membership functions. Finally, MCDM techniques were employed to rank the risks, and fuzzy logic was utilised to ascertain risk levels. The final matrix offers a clear visual depiction of the severity and probability of various climate risks.

3.2. Variables Selection (Climate Transition Risk Identification)

The initial step in developing a risk management plan is to classify the sources of risk within an organisation. To achieve this, we conducted an extensive review of the literature to identify the major risks of climate change that affect the processed food industry. This enabled us to identify the relevant variables to be considered in our system and rank them according to their severity. Risks were identified for the four types of risks that make up the climate transition risk, which are regulatory, technological, market, and reputational risk.

3.3. Multi-Criteria Decision-Making Methods and Their Comparison

The choice of the MCDM methods was guided by several important criteria: the capacity to manage multiple variables, adaptability to various contexts, and robustness in evaluating complex risks. The selected methods were chosen due to their broad acceptance in the academic literature and their relevance to climate risk studies. Each method was assessed based on how well it aligned with our research goals, particularly its capability to offer a detailed and quantitative classification of climate risks.

We employ a variety of MCDM methods to guarantee a thorough and resilient evaluation of climate risks. Each method brings its own viewpoint and tackles different facets of the issue, collectively offering a more detailed and nuanced understanding. By utilising these diverse approaches, we can compare and contrast outcomes, ensuring that the final decisions are well-informed and more dependable.

This study considers a varied set of multiple state-of-the-art MCDM methods that have very different logic and combine them with fuzzy logic to construct a climate transition risk matrix. These methods are listed below.

- Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [45];

- Complex Proportional Assessment (COPRAS) [46];
- Borda count method (BORDA) [48];
- Simple additive weighting (SAW) [49];
- Élimination et Choix Traduisant la Realité (ELECTRE) [50];
- Vice Kriterijumsa Optimizacija I Kompromisno Resenje (VIKOR) [50];
- Measurement Alternatives and Ranking According to the Compromise Solution (MARCOS) [52];
- Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) [53];
- Weighted Sum Model (WSM) [51];
- Combinative Distance-Based Assessment (CODAS) [54].

The Python *pyDecision* library is used to allow a fair and extensive comparison of the different methods and variables considered. This comparative analysis includes established approaches from the literature, where the weights used in the risk assessment process are traditionally obtained with an FL-based system, and our innovative approach that uses TOPIS to obtain a weight for each risk variable. Using *pyDecision*, we can rank each of the methods under consideration (that is, the Kendall rank correlation coefficient [56] is used to measure the association with the number of concordances and discordances in the paired observations) and select the most appropriate one for the case at hand.

This analysis of risk prioritisation systems enables us to evaluate the current state of the field and comprehend how far along it is based on the judgements and views expressed by experts in the literature.

3.4. Data Collection

A validation questionnaire was designed to collect feedback from experts from a Colombian organisation (the organisation providing us with feedback and data decided to remain anonymous) in the sector. The questionnaire consists of six sections, and a facsimile version can be viewed and taken from [57]. The individuals who completed the questionnaire were selected because they had experience and area-specific knowledge associated with this type of risk. A total of 16 experts from different areas of the organisation participated in the study, with the aim of capturing as much knowledge as possible.

3.4.1. Dataset Preparation

The real data, that is, in the form obtained from this collection phase, could not be directly used and disclosed in this article to avoid leaks of confidential information, as previously agreed with the organisation supporting this research.

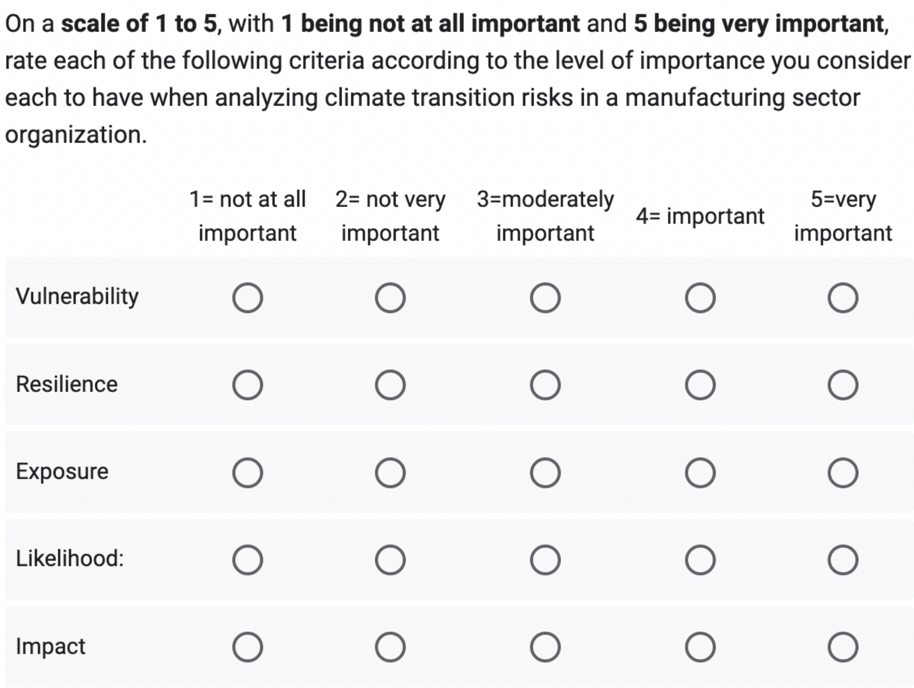
Therefore, the real dataset was modelled by deriving the corresponding distributions to be used to generate all the data for this study instead. The latter imitates the original dataset, being equally distributed, and it is not subject to any non-disclosure agreement. We discussed this with our business partners, who agreed to adopt this approach.

3.4.2. Design Considerations on the Data Collection Form

The first section of the questionnaire is designed to evaluate the five criteria chosen to analyse the risk variables: vulnerability, resilience, exposure, probability, and impact. These are key to risk assessment in organisations and should all be considered when performing a detailed analysis aimed at a high-quality assessment. In fact, it is vital to consider probability, noting that risk is not limited to hazard and exposure alone, as there are other important aspects to consider, such as vulnerability, resilience, and financial impact [58]. It should be noted that the Intergovernmental Panel on Climate Change (IPCC) argues that the risks of climate disasters are composed of exposure, vulnerability, and risk. This approach is also useful for assessing the financial impacts of climate transition risks. Often, economic and financial analyses consider only the exposure of an organisation, but it is essential to consider vulnerability, resilience, and economic impact to fully understand the potential materialisation of these climate-related risks, as these concepts are interdependent.

For example, if a company is less resilient than others, then its exposure may be higher; if a company is more vulnerable, then its exposure may also be higher [59].

Due to the considerations above, we decided to determine the importance of the risk assessment criteria with feedback from experts in the field. Therefore, in the first section of the questionnaire, they were asked to rate the criteria on a "Likert scale" ranging from 1 to 5, with 1 representing the minimum importance and 5 representing the maximum importance (see Figure 2).



On a **scale of 1 to 5**, with **1 being not at all important** and **5 being very important**, rate each of the following criteria according to the level of importance you consider each to have when analyzing climate transition risks in a manufacturing sector organization.

	1= not at all important	2= not very important	3=moderately important	4= important	5=very important
Vulnerability	○	○	○	○	○
Resilience	○	○	○	○	○
Exposure	○	○	○	○	○
Likelihood:	○	○	○	○	○
Impact	○	○	○	○	○

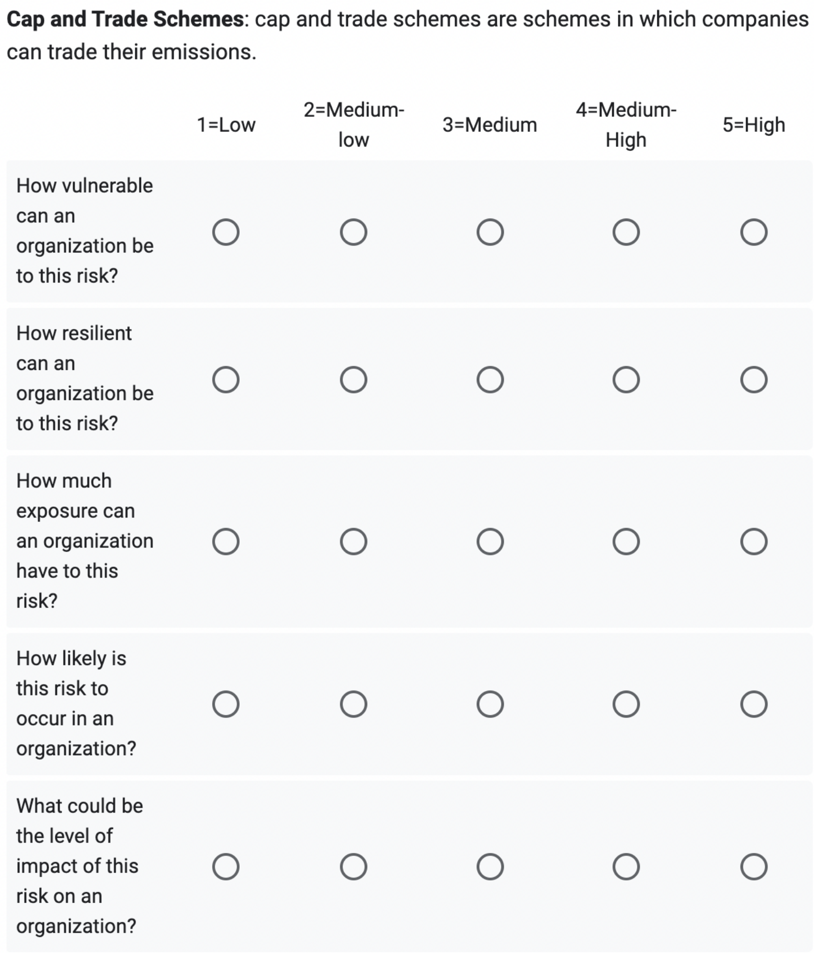
Figure 2. Section 1 of the questionnaire: transitional climate risk criteria rating.

In the second section of the data collection form, we introduce four regulatory climate risks (see example of one of the risks analysed in regulatory risks in Figure 3).

In this section, assessors were asked to rate criteria on a scale of 1 to 5, with 1 being the lowest rating and 5 being the highest for each criterion. The financial effect of each risk on an organisation is reflected in the qualitative ratings. It is worth pointing out that what may be considered as having a high impact by one expert may be considered to have a medium impact by another. Therefore, because of their "fuzzy" nature, we agreed that converting them into fuzzy variables would be the most logical approach.

Similar considerations were made for each of the four remaining variables when deciding what to include in the questionnaire form. With reference to [57], one can see that variables such as market and reputation are addressed in sections 3, 4, and 5 of the proposed questionnaire.

Finally, the sixth section of the form focuses on defining the rules to use in the fuzzy logic model. In this section, experts were asked to assign the level of risk (low, medium, high, or critical) to the 25 combinations of rules introduced in Section 4 of this manuscript.



Cap and Trade Schemes: cap and trade schemes are schemes in which companies can trade their emissions.

	1=Low	2=Medium-low	3=Medium	4=Medium-High	5=High
How vulnerable can an organization be to this risk?	○	○	○	○	○
How resilient can an organization be to this risk?	○	○	○	○	○
How much exposure can an organization have to this risk?	○	○	○	○	○
How likely is this risk to occur in an organization?	○	○	○	○	○
What could be the level of impact of this risk on an organization?	○	○	○	○	○

Figure 3. Section 2 of the questionnaire: regulatory risks.

4. The Proposed Fuzzy System

Perception of risk and the relationship between its variables can vary between individuals. Fuzzy logic is a valuable tool in risk management and assessment because it allows the use of human expertise to create fuzzy IF–THEN rules. It is essential to take advantage of the knowledge of risk managers and experts and convert it into rules that can be used by a fuzzy inference system (FIS) to automate risk assessment.

The application of fuzzy logic in the risk evaluation process was executed through multiple phases. Initially, the input data were converted into fuzzy values using normalised trapezoidal membership functions. Next, IF–THEN fuzzy rules were employed to translate these input values into output fuzzy sets. Lastly, the centroid method was utilised for defuzzification, resulting in a distinct numerical value for each risk.

Let x_i be an input variable representing a risk metric (e.g., frequency or severity). This variable is converted into a fuzzy value $\mu_{A_i}(x_i)$ using a trapezoidal membership function, defined as

$$\mu_{A_i}(x_i) = \begin{cases} 0, & \text{if } x_i \leq a_1 \text{ or } x_i \geq a_4, \\ \frac{x_i - a_1}{a_2 - a_1}, & \text{if } a_1 < x_i \leq a_2, \\ 1, & \text{if } a_2 < x_i \leq a_3, \\ \frac{a_4 - x_i}{a_4 - a_3}, & \text{if } a_3 < x_i \leq a_4. \end{cases} \tag{1}$$

where a_1, a_2, a_3, and a_4 are the parameters defining the trapezoidal membership function.

For the sake of reproducibility, the code that implements the FIS described in the rest of this article is made available as an attachment to the online version of this manuscript.

Fuzzy logic was employed to manage the uncertainty intrinsic to climate risk evaluation. This approach enabled us to deal with vague and subjective information, capturing uncertainty with fuzzy sets and membership functions. Utilising IF–THEN rules and the centroid method for defuzzification, we can achieve more precise and realistic risk evaluations, taking into account the variability and uncertainty of the data at hand.

Figure 4 summarises the methodology proposed for our study.

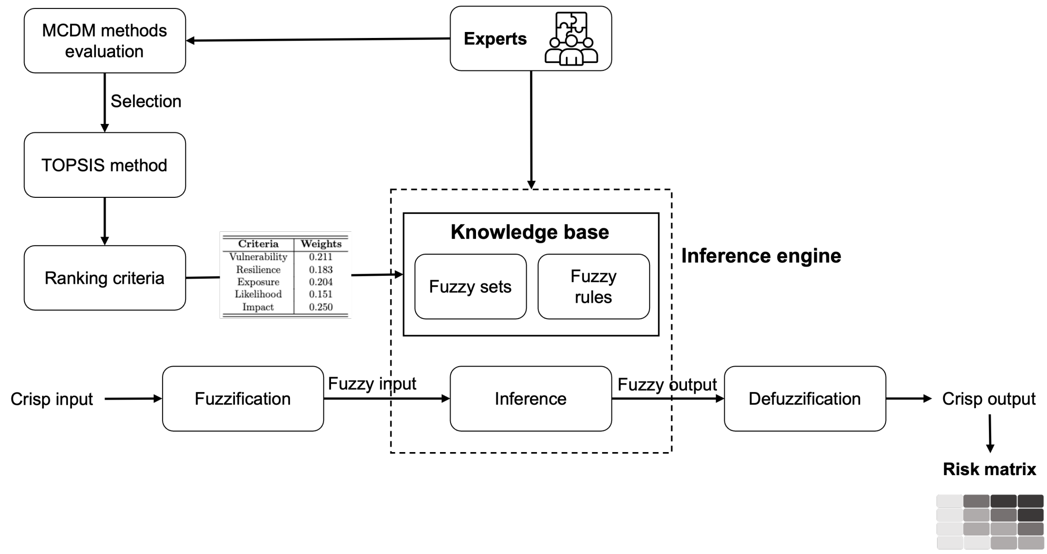


Figure 4. The proposed methodology—an overview.

4.1. Fuzzy Risk Matrix Sets Definition (Fuzzification)

After assessing the risks with the help of experts, we proceed to the fuzzification stage. In this stage, the data are transformed into fuzzy values by mapping the input values into fuzzy set membership functions. These fuzzy values are then processed by the reasoning system, also known as FIS [60].

To create a fuzzy risk matrix, it is necessary to select the relevant and available input variables and divide their range into fuzzy sets. In addition, different forms of membership functions can be used, depending on the characteristics of the variables, and this choice depends on the applications where the fuzzy systems will be implemented. For the case of risk analysis, the normalised trapezoidal membership function type is generally used, which is a commonly used option to quantify the certainty of expert opinions. These membership functions are represented by a tuple $(a1, a2, a3, a4)$, where $a1 \leq a2 \leq a3 \leq a4$, and have a height of 1. This choice is considered the most natural for this type of system [61].

Normalised trapezoidal membership functions were selected due to their capability to effectively capture uncertainty and ambiguity in the input data. These functions enable a seamless transition between various risk levels, which is crucial for evaluating climate risks with indistinct boundaries. The selection of trapezoidal functions aids in the interpretation and analysis of the outcomes, offering a more precise and flexible depiction of the fuzzy data.

4.2. Fuzzy Inference System

An FIS uses rules based on risk knowledge to map fuzzy input sets (frequency and severity) to fuzzy output risk sets. This is accomplished by using fuzzy IF–THEN rules. The fuzzy rule structure for the fuzzy risk matrix is as follows: IF the probability is $\overline{p}_n$ AND the impact of the consequences is $\overline{i}_n$ THEN the risk level is $\overline{r}_n$, where $\overline{p}_n$, $\overline{i}_n$, and $\overline{r}_n$ are the fuzzy sets for the probability, impact, and risk level defined over the discourse universes, respectively [9].

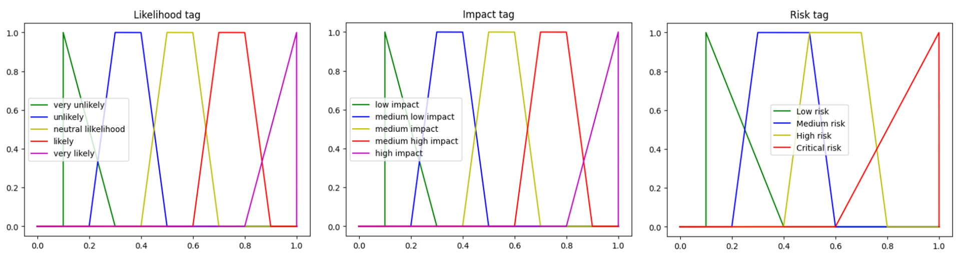
In this case, five levels of probability and five levels of impact are used, generating a total of 25 rules representing the risk categories. These fuzzy rules capture the knowledge and experience of experts through linguistic variables and are combined with data analysis to obtain more accurate and realistic results (see Table 2).

Table 2. Fuzzy rules set.

Rule	Description
1	IF the likelihood is low and the impact is low, THEN the risk level is low
2	IF the likelihood is low and the impact is low-medium, THEN the risk level is low
3	IF the likelihood is low and the impact is medium, THEN the risk level is low
4	IF the likelihood is low and the impact is medium–high, THEN the risk level is medium
5	IF the likelihood is low and the impact is high, THEN the risk level is medium
6	IF the likelihood is low–medium and the impact is low, THEN the risk level is low
7	IF the likelihood is low–medium and the impact is low–medium, THEN the risk level is low
8	IF the likelihood is low–medium and the impact is medium, THEN the risk level is medium
9	IF the likelihood is low–medium and the impact is medium–high, THEN the risk level is medium
10	IF the likelihood is low–medium and the impact is high, THEN the risk level is high
11	IF the likelihood is medium and the impact is low, THEN the risk level is low
12	IF the likelihood is medium and the impact is low–medium, THEN the risk level is low
13	IF the likelihood is medium and the impact is medium, THEN the risk level is medium
14	IF the likelihood is medium and the impact is medium.high, THEN the risk level is high
15	IF the likelihood is medium and the impact is high, THEN the risk level is high
16	IF the likelihood is medium–high and the impact is low, THEN the risk level is low
17	IF the likelihood is medium–high and the impact is low–medium, THEN the risk level is medium
18	IF the likelihood is medium–high and the impact is medium, THEN the risk level is medium
19	IF the likelihood is medium–high and the impact is medium–high, THEN the risk level is high
20	IF the likelihood is medium–high and the impact is high, THEN the risk level is critical
21	IF the likelihood is high and the impact is low, THEN the risk level is low
22	IF the likelihood is high and the impact is low–medium, THEN the risk level is medium
23	IF the likelihood is high and the impact is medium, THEN the risk level is high
24	IF the likelihood is high and the impact is medium–high, THEN the risk level is critical
25	IF the likelihood is high and the impact is high, THEN the risk level is critical

Mamdani's fuzzy inference algorithm is used to convert qualitative rules into quantitative results. Mamdani systems are advantageous for expert system applications due to their intuitive and straightforward rule bases, which are derived from human expert knowledge. This model employs the min operator for AND logic and the implication of the output set. The output fuzzy sets are aggregated from the evaluated rules. The aggregate membership function for an output fuzzy risk category is calculated using the maximum of the minima between the frequency sets, severity sets, and risk sets (see Equation (8)). The model was implemented using the "sckit-fuzzy" library in Python.

In addition, the graph of Figure 5 shows the membership functions. Linguistic terms provide a more adaptable and precise way to represent risks, which can often be ambiguous or subjective. For example, instead of assigning a specific probability to a risk, we can describe it as 'high', 'medium', or 'low', which aligns better with the uncertain nature of climate risks. In this case, a study involving a processed food company in Colombia, phrases such as 'very likely' or 'significant impact' were used to assess the identified risks. This approach improved communication and understanding among experts and made the risk assessment process more effective.



(a) Probability (b) Impact (c) Risk level

Figure 5. Membership functions.

In particular, Figure 5a shows the trapezoidal membership functions of the first entry of the risk matrix, which was designed based on an FIS related to the probability of the risk on a level of five scales: very unlikely, unlikely, neutral probability, probable, and very probable.

On the other hand, Figure 5b shows the membership functions of the second entry of the risk matrix, with respect to the impact on the low, medium–low, medium–high, and high scale.

Finally, Figure 5c shows the third component of the membership functions of the matrix fuzzy system model, the risk levels, which are represented on the scale low, medium, high, and critical.

Table 3 summarises the classification and descriptions of the risk levels identified by the case study organisation.

Table 3. Risk levels.

Risk Level	Description
Low	The probability that an adverse event will occur is low and the consequences are minimal or manageable. This type of risk can be easily mitigated with preventive measures.
Medium	The probability that an adverse event will occur is moderate, with significant but not severe consequences. Adequate risk management is required to reduce the probability of occurrence and mitigate impacts.
High	The probability that an adverse event will occur is high and has significant consequences. A careful risk management and a proactive approach are required to minimise risk and possible negative consequences.
Critical	The probability that an adverse event will occur is extremely high and has catastrophic consequences. These can include both severe financial losses and a deleterious impact on the environment. This type of risk requires rigorous management and complete contingency planning.

The inference engine of the system evaluates each rule stored in the knowledge base and performs fuzzy inference. This is achieved by determining the strength of each fuzzy rule, considering the degree of coincidence and the fuzzy connectors used in the antecedents of the rule. This allows decisions to be made in a system that considers not only true or false values, but also fuzzy values [62].

The defuzzification module of the model is responsible for producing a single-scalar output or a crisp value based on the inference result. Since in the fuzzification module, the crisp values of the input variables are fuzzified into the fuzzy sets, this final stage extracts the precise value from the range of the fuzzy set for the output variable. In this case, the centroid method, also known as the centre of the area (CAO) method or centre of gravity, is used since the centroid is the point along the x-axis around which the fuzzy set would balance [62].

According to [9], the COA calculates the weighted average of a fuzzy set. The result of applying the COA defuzzification to the risk index can be expressed with Equation (2), which is shown below.

$$r = \frac{\int \mu_{\overline{R}}(r) r dr}{\int \mu_{\overline{R}}(r) r dr} \tag{2}$$

The questionnaire form introduced in Section 3.4 was used to collect feedback from experts to create our dataset and produce results through our proposed system.

4.3. TOPSIS Method

TOPSIS is based on the premise that the selected options should be as close as possible to the positive ideal solution and as distant as possible from the negative ideal solution. The chosen alternatives can be ranked and assessed based on their relative proximity to the ideal solution. The following are the detailed steps to follow.

Obtain a standardised matrix. The standardised value $a_i j$ is calculated as

$$a_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m}(x_{ij})^2}} \quad (1 \leq i \leq m, 1 \leq j \leq n) \tag{3}$$

Calculate the weighted standardised matrix D:

$$D = (a_{ij} \times w_j) \quad (1 \leq i \leq m, 1 \leq j \leq n) \tag{4}$$

where w_j is the weight of the criteria and $\sum_{i=1}^{n} w_j = 1$.

Calculate the positive ideal solution V^* and the negative ideal solution V^-:

$$V^* = \{v_1^*, v_2^*, \ldots, v_n^*\} = \left\{\max_i v_{ij} \mid j \in J, \min_i v_{ij} \mid j \in J'\right\} \tag{5}$$

$$V^- = \{v_1^-, v_2^-, \ldots, v_n^-\} = \left\{\min_i v_{ij} \mid j \in J, \max_i v_{ij} \mid j \in J'\right\} \tag{6}$$

Calculate the separation measures by applying the m-dimensional Euclidean distance.

$$S_i^+ = \sqrt{\sum_{j=1}^{n}(V_i^j - V^*)^2} \quad (1 \leq i \leq m, 1 \leq j \leq n) \tag{7}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n}(V_i^j - V^-)^2} \quad (1 \leq i \leq m, 1 \leq j \leq n) \tag{8}$$

Calculate the relative proximity,

$$Y_i = \frac{S_i^-}{S_i^+ - S_i^-} \quad (1 \leq i \leq m), \tag{9}$$

where $Y_i \in (0, 1)$; the closer Y_i is to 1, the closer the alternative is to the ideal solution.

Prioritisation ranking: the greater Y_i, the better the chosen alternative.

5. Experimental Phase and Results Discussion

Our results refer to the data and methods described in Section 3.

5.1. Selected Variables

A critical step in managing climate transition risks in an organisation is to categorise and prioritise risk sources, allowing the allocation of the necessary resources to mitigate their impacts [60]. In this regard, variables based on each of the four types of risks were identified during the review of the literature.

Table 4 shows the variables selected for expert evaluation using the questionnaire explained in Section 3.4. The risks are classified by type, including regulatory, technological, market, and reputational risks, as well as their description and the sources supporting their selection.

Table 4. Climate transition variables selected.

Risk Name	Risk Type	Description	Sources
Cap and trade schemes	Regulatory	Emission trading systems with pre-established caps are systems in which companies can trade their emissions	[1–3]
Carbon tax increase		Regulatory strategy to reduce greenhouse gas emissions from companies	[1–4,23,30–34] [25,26,35–41]
Climate change-related litigation		Legal risks for non-compliance with climate change-related responsibilities, including harm to individuals or the environment	[3,23,33,39,42]
Obligation to report emissions		Companies are obliged to disclose the greenhouse gas emissions they produce to comply with general regulations or identify any excess emissions	[1,2,13,24,35]

Table 4. *Cont.*

Risk Name	Risk Type	Description	Sources
Shift to less carbon-intensive production or consumption patterns	Technological	Use of fuels with lower greenhouse gas emission factors for thermal energy generation	[1,2,14]
Technological progress in renewable energies and energy efficiency		Investments in products, processes, or services aimed at reducing carbon footprint and improving environmental conditions, but that do not meet expectations	[1,2,14,34]
Technological change (development of new technology)		New technological advancements that enable improved outcomes in the company's energy processes	[3,4,14,15,41]
Failed investments in new technologies to reduce emissions		Development of new technologies with a less harmful impact on climate or the environment, rendering them obsolete or uncompetitive (stranded assets)	[16,17,23,26,36,38]
Change in the demand for products and services	Market	Changes in the demand for products and services driven by concerns about climate change	[1,3,13,23,24,26,27,30,41]
Raw materials and supplies (price volatility and availability)		Changes in prices, demand, volatility, and other aspects related to climate change that impact the supply of raw materials	[1,2,13,30]
Stakeholder concerns on climate change		Concern among market stakeholders and/or other affected government and social groups, creating uncertainty	[1–3,23,34]
Poor adaptation to change in customers' behavior		Limited adaptability of business models to changing needs, desires, and customer behaviors regarding climate change	[1,2]
Changes in customer preferences	Reputational	Reputation risk from loss or change in preference for a company's product	[1,2,4,15,23,28–30,33]
Increasing pressure from non-governmental organisations		Pressure exerted by non-governmental organisations on companies' actions with environmental impact generates media attention and cause reputational harm	[24]
Negative news and comments Information about the company		News on environmental responsibility enhances shareholder value, while negative news can have a deleterious impact on it	[1,2,13,16]
Changes in market sentiment due to potential future climate risks		Shifts in sentiment due to awareness of climate issues that the future may hold if we cannot react promptly	[34]

5.2. Calculation of Criteria Weights

First, the TOPSIS method was used to perform calculations to determine the scores according to the individual importance assigned by the experts and the ranking of the criteria determined by the climate transition risk assessment. The experts used a scale from 1 to 5 to rate each criterion, where 1 means "not at all important" and 5 means "very important". Table 5 shows the weights of the criteria as a result of applying the TOPSIS method. The modelling of the TOPSIS method equations was coded using the Python programming language to facilitate the calculations involved.

Table 5. Ranking criteria.

Criteria	Weights
Vulnerability	0.211
Resilience	0.183
Exposure	0.204
Likelihood	0.151
Impact	0.250

According to the weights assigned to the criteria, likelihood is the criterion with the lowest weight. It is important to note that both probability and impact are criteria used to determine the level of risk in multiple variables and in most risk assessment contexts. However, according to [58], the impact is the result of the interaction between vulnerability, resilience, and exposure. This means that the results of the analysis can be interpreted as consistent from a theoretical point of view.

5.3. MCDM Method Comparison

The similarity or difference between different MCDM methods can be determined using various metrics, such as correlation coefficients. By examining the ranking table of the 10 selected methods, those that classify alternatives similarly are COPRAS, SAW, MARCOS, and WSM. On the other hand, some methods, such as VIKOR, PROMETHEE, and ELECTRE, appear to classify these variables differently from the others. However, the choice of the most similar or dissimilar methods depends on the method chosen to measure this similarity.

The RM2 risk is consistently high in most of the methods evaluated, as it is always in the first and second positions. On the other hand, the alternative or variable Rrep4 for reputational climate risk consistently ranks last in all methodologies.

There are clear distinctions between the techniques used for analysis. For example, the RM2 risk is generally the most appropriate option by most methods, with the exception of TOPSIS, BORDA, VIKOR, and PROMETHEE. These discrepancies may be due to variations in decision criteria, weighting methods [63], or even the decision matrix, which differs from method to method. MCDM methods have different mathematical approaches, decision-making principles, focus on different aspects, and also have different advantages and disadvantages. Some methods take into account the relative importance (weights) of the criteria, while others do not. This can result in different methods producing different rankings or evaluations of alternatives and is one of the main causes of inconsistent results.

The complexity of real-world problems, the accuracy of the data, the possible relationships between criteria, the variation of trade-off indices, and different types of scales can all influence the results. In this scenario of the climate transition risk analysis, there is consensus among most of the methods. Looking at the results, it is clear that the risk RM2 is ranked number 1 by most methods (6/10), the risk Reg2 is ranked number 2 (7/10 methods), and the risk RT3 is ranked number 3 (9/10 methods); see Table 6.

Table 6. Ranking of MCDM methods.

Risk Description	Code	TOPSIS	COPRAS	BORDA	SAW	ELECTRE	VIKOR	MARCOS	PROMETHEE	WSM	CODAS
Cap and trade schemes	Rreg1	6	7	7	7	8	10	7	6	7	7
Carbon tax increase	Rreg2	1	2	1	2	2	2	2	1	2	2
Climate change-related litigation	Rreg3	12	12	13	12	15	7	12	13	12	12
Obligation to report emissions	Rreg4	10	10	10	10	10	11	10	11	10	10
Shift to less carbon-intensive production or consumption patterns	RT1	5	5	5	5	4	5	5	5	5	4
Technological progress in renewable energies and energy efficiency	RT2	7	6	6	6	7	6	6	7	6	6
Technological change (development of new technology)	RT3	3	3	3	3	3	1	3	3	3	3
Failed investments in new technologies to reduce emissions	RT4	13	13	12	13	12	14	13	12	13	13
Change in the demand for products and services	RM1	14	15	14	15	13	15	15	14	15	14
Raw materials and supplies (price volatility and availability)	RM2	2	1	2	1	1	4	1	2	1	1
Stakeholder concerns on climate change	RM3	4	4	4	4	5	13	4	4	4	5
Poor adaptation to change in customers's behaviour	RM4	15	14	15	14	14	3	14	15	14	15
Changes in customers preferences	Rrep1	11	11	11	11	11	8	11	10	11	11
Increasing pressure from non-governmental organisations	Rrep2	8	8	8	8	6	12	9	8	8	9
Negative news and comments Information about the company	Rrep3	9	9	9	9	9	9	9	9	9	8
Changes in market sentiment due to potential future climate risks	Rrep4	16	16	16	16	16	16	16	16	16	16

The comparative study of the outcomes derived from various MCDM methods shows notable differences in risk classification due to each method's unique strengths and weaknesses. TOPSIS and SAW are notable for their simplicity and efficiency in managing large datasets, identifying price volatility (RM2) as the most crucial risk. In contrast, VIKOR and PROMETHEE, despite being more intricate, are favoured in scenarios with conflicting criteria, emphasising the significance of regulatory risk (Rreg2). COPRAS and FRAMES, though less straightforward, enable direct comparisons based on proportional relationships and incorporate ideal and anti-ideal solutions, respectively, offering a comprehensive and balanced evaluation.

Due to their simplicity, the BORDA and WSM methods are straightforward to use but might oversimplify intricate issues, both identifying RM2 as a significant risk. Conversely, ELECTRE and CODAS, being robust and detailed, necessitate a deeper understanding and more intensive calculations, emphasising regulatory and technological risks as critical. This variation underscores the necessity of selecting the appropriate MCDM method based on the specific context and goals, offering a nuanced and comprehensive perspective that enables decision-makers to choose the optimal mitigation strategy for each type of risk.

However, it is important to analyse the correlation between the MCDM methods; the following figure shows the correlation coefficients of the different methods evaluated (Figure 6).

	TOPSIS	COPRAS	BORDA	SAW	VIKOR	MARCOS	PROMETHEE	WSM	CODAS
TOPSIS	1.00	0.95	0.97	0.95	0.42	0.95	0.97	0.95	0.93
COPRAS	0.95	1.00	0.95	1.00	0.43	1.00	0.92	1.00	0.95
BORDA	0.97	0.95	1.00	0.95	0.42	0.95	0.97	0.95	0.93
SAW	0.95	1.00	0.95	1.00	0.43	1.00	0.92	1.00	0.95
VIKOR	0.42	0.43	0.42	0.43	1.00	0.43	0.42	0.43	0.45
MARCOS	0.95	1.00	0.95	1.00	0.43	1.00	0.92	1.00	0.95
PROMETHEE	0.97	0.92	0.97	0.92	0.42	0.92	1.00	0.92	0.90
WSM	0.95	1.00	0.95	1.00	0.43	1.00	0.92	1.00	0.95
CODAS	0.93	0.95	0.93	0.95	0.45	0.95	0.90	0.95	1.00

Figure 6. Correlation matrix.

Examining the correlation of weights between different MCDM techniques provides information to understand the similarities and differences between MCDM methods. Each method has its own algorithm and analytical approach for assigning weights to each decision criterion, which shows the relative importance of each criterion. Thus, the correlation of weights between different methods can be a useful indicator of the degree of agreement between these methods in prioritising decision criteria.

The rankings produced by the different MCDM methods show a high correlation, which implies that the options are considered similar due to their characteristics. This could be an indication of the reliability and robustness of the results, as different methods with different assumptions and procedures produce similar results.

It is important to keep in mind that although a strong correlation may be reassuring, no MCDM approach should be considered the "correct" one. There may be elements that affect the overall score of an option that are not taken into account or are not fully taken into account by the different MCDM techniques. Therefore, it is still necessary to understand the assumptions of each method and interpret the results accordingly. For example, some techniques may be more appropriate for certain types of decision contexts or depend on the availability of certain types of data or its quality.

Considering that MCDM methods only allow the generation of a ranking of alternatives, there is a limitation in the construction of risk matrices, as the results are not classified by risk level (low, medium, high, and critical), as shown in the risk matrix in Figure 1. However, based on the results of the analysis of all MCDM methods, it can be determined that the risks RM2, Reg2, RT3, and RM3 are the most critical risks for the organisation of this sector. On the other hand, risks RT1, RT2, and Reg1 could be classified in the high level of the risk matrix, followed by risks Rrep2, Rrep3, Reg4, Rrep1, Rep3, RT4, RM4, RM1, and Rrep4, in the medium level of the risk matrix.

Comparing the results generated by the MCDM and fuzzy logic methods, we can see that RM2 and Reg2 are the most critical risks according to the results. However, not all risks were in the same order; in fact, only the risks RT4 and Rrep4 coincided, which were placed at positions 11 and 16, respectively, in both techniques used. However, the advantages of using methods such as fuzzy logic are the possibility not only to generate a ranking of alternatives, risks in this case, but also to classify them in different risk scales, as sought in this study. Furthermore, the results obtained with fuzzy logic coincide to a certain extent with those reported in the literature and by different organisations that analyse and monitor climate transition risks. The results obtained with the fuzzy logic method, which was selected for this study, are analysed below.

Fuzzy MCDM Methods

Many studies have combined fuzzy logic with various MCDM techniques, using the latter for the prioritisation of a set of alternatives. Determining the relative importance of various criteria in MCDM problems implies a high degree of subjectivity derived from the personal preferences of decision-makers. However, the values of linguistic variables in expert judgement are often vague, representing interval values rather than fixed values; therefore, fuzzy MCDM methods often deal with this uncertain, imprecise, and vague information in decision-making problems [64]. Among the different hybrid methods, we find combinations of fuzzy logic with TOPSIS, AHP, ELECTRE, VIKOR, COPRAS, and VSM, among others.

Usually, when applying the Fuzzy-TOPSIS method (FT), the membership function is constructed first in the fuzzy method, then the calculations of the fuzzy risk priority numbers are performed by multiplying the probability and impact membership functions, and finally, these fuzzy risk-level results are prioritised using the TOPSIS method [65].

Table 7 shows the results of applying the FT method and the conventional TOPSIS method, showing a difference in the classification results. On the one hand, the risk prioritised by the FT method is market risk 3 (RM3), while in the TOPSIS method it is regulatory risk 2 (Rreg2). On the other hand, the second most important risks for the FT and TOPSIS methods were regulatory risk 2 (Rreg2) and market risk 2 (RM2), respectively. Overall, there are some similarities in the results, but given the differences in the application of the methods, there are obvious discrepancies.

In fact, the results of the Fuzzy-TOPSIS method differ to some extent from the results of the previously tested MCDM methods and the modified fuzzy method in this study. In this scenario, the results of the TOPSIS method are more consistent with the results of the previous section and with the individual responses of the consulted experts; for this reason, TOPSIS is selected as a complement to generate the weights in the fuzzy method proposed in this study. The final results obtained are discussed in the following subsection.

Table 7. Fuzzy-TOPSIS vs. TOPSIS methods.

Risk Code	Rank	
	Fuzzy-TOPSIS	**TOPSIS**
Rreg1	8	6
Rreg2	2	1
Rreg3	15	12
Rreg4	14	10
RT1	16	5
RT2	7	7
RT3	6	3
RT4	12	13
RM1	11	14
RM2	5	2
RM3	1	4
RM4	10	15
Rrep1	9	11
Rrep2	4	8
Rrep3	3	9
Rrep4	13	16

5.4. Fuzzy Risk Matrix Analysis

In this study, we used the centre of the area, also known as centroid defuzzification, which produces as a result a single numerical value corresponding to the fuzzy sets. Table 8 reports these numerical values for each of the 16 risks evaluated. Note that these results are obtained by processing the data from the procedure described in Section 3.4 with the proposed TOPSIS approach, which allowed us to quantify the probability and impact criteria evaluated by the experts completing our questionnaire. The TOPSIS method was selected as an alternative for determining the weights because, when analysing the results of the experts' opinions, it was clear that the opinions were very much in line with the weighting carried out by the TOPSIS method. These results reflect the concrete data obtained after applying the fuzzy inference model in the analysis of identified risks.

Table 8. Crisp risk values.

Risk Code	Likelihood		Impact		Risk level	
	%	**Linguistic**	**%**	**Linguistic**	**%**	**Linguistic**
Rreg1	0.3929	Unlikely	0.9371	High	0.6000	High
Rreg2	0.7321	Likely	0.9720	High impact	0.8644	Critical
Rreg3	0.2000	Very unlikely	0.8252	Medium–high	0.4000	Medium
Rreg4	0.6071	Medium	0.7552	Medium–high	0.6000	High
RT1	0.8393	Likely	0.9720	High	0.8519	Critical
RT2	0.4643	Medium	0.9091	High	0.6000	High
RT3	0.6786	Likely	0.9441	High	0.7883	Critical
RT4	0.2000	Very unlikely	0.8252	Medium–high	0.4000	Medium

Table 8. *Cont.*

Risk Code	Likelihood		Impact		Risk level	
	%	Linguistic	%	Linguistic	%	Linguistic
RM1	0.2321	Very unlikely	0.8392	Medium–high	0.4696	Medium
RM2	1.0000	Very unlikely	1.0000	High	0.8667	Critical
RM3	0.4286	Unlikely	0.8741	High impact	0.5202	High
RM4	0.2000	Very unlikely	0.8042	Medium–high	0.4000	Medium
Rrep1	0.2143	Very unlikely	0.8531	Medium–high	0.4461	Medium
Rrep2	0.4286	Unlikely	0.8182	Medium–high	0.4559	Medium
Rrep3	0.3750	Unlikely	0.7832	Medium–high	0.4000	Medium
Rrep4	0.2000	Very unlikely	0.6853	Medium–high	0.3797	Medium

The above values were arranged in descending order to identify the most dominant risks, which are represented in the risk matrix shown in Figure 7. When applying the fuzzy logic model and comparing it with the TOPSIS model, it was determined that the most critical and priority risks, in descending order, were RM2, RT3, Rreg2, and RT1, as can be seen in the red highlighted section in the matrix. These risks have a high probability of occurrence and a significant negative impact on the organisation, which is consistent with what has been reported in the specialised literature.

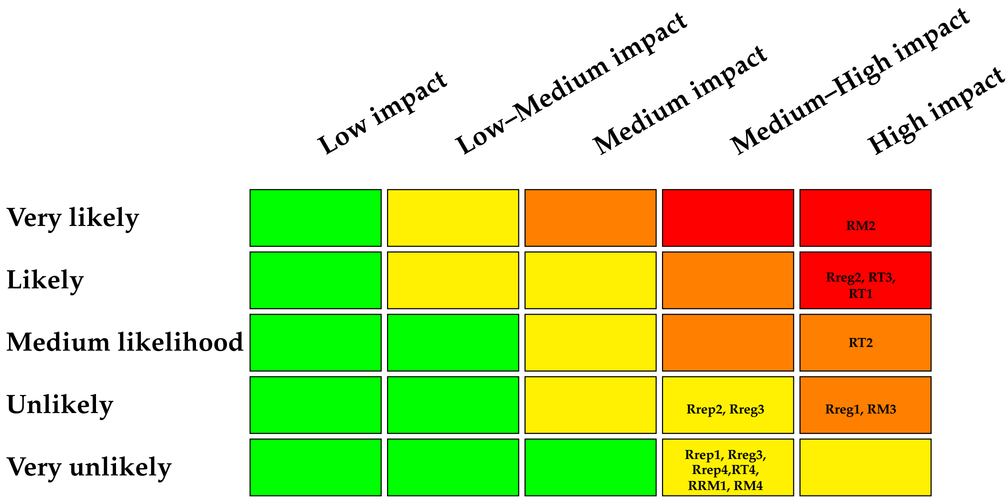


Figure 7. Climate transition risk matrix. Green is used to indicate low risk, yellow to indicate medium risk, orange to indicate high risk, and red to indicate critical risk.

In terms of the most critical risk according to the results of experts' opinions, changes in prices, demand, volatility, and other aspects related to climate change will affect the availability of raw materials and inputs for companies (RM2), generating uncertainty and increased costs of these supplies, increasing costs and production capacity, due to changes in prices of certain inputs such as energy, water, and fuels. However, none of the methodologies we have evaluated so far considers the market approach from this perspective, as it is associated with the misperception of market climate risk as a long-term risk.

In relation to the increase in the carbon tax (Rreg2), which is a regulatory strategy that seeks to reduce GHG emissions by companies, studies such as ours establish that one of the impacts of this risk is a reduction in operating margin due to a higher cost of CO_2 emissions; a reduction in the prices of investments and shares and few profits, and higher interest rates, which in turn could limit access to financing and increase the cost of such financing. Due to the additional payments resulting from the carbon tax, companies could face higher default costs and higher insurance premiums, as well as a possible impact on credit quality with high GHG emissions.

It should be noted that most existing methodologies that estimate climate risk only employ the regulatory variable of carbon tax. However, according to [66,67], carbon emissions do not capture all aspects of climate transition risk; they are only a proxy of climate-related regulatory risks given the multiple drivers and transmission channels, such as the potential for technological innovation and litigation.

However, in terms of the risks of RT1, RT2, and RT3, unexpected or very rapid changes in technological innovations related to climate, companies may also have economic and financial consequences, regardless of climate-related regulations. These innovations can turn companies' assets into obsolete or stranded assets (RT3), resulting in lower profit margins, higher operating costs, and financial destabilisation of the company.

On the other hand, the transition to less carbon-intensive energy-based production patterns (RT1), which consists of the use of fuels with better GHG emission factors for the generation of thermal power in companies, would entail costs associated with the adoption of this new technology. However, companies that rely on these types of processes and carbon-intensive technologies may become less competitive if they do not adopt these technological innovations.

Complementing the analysis, the risks Rreg1, Rreg4, RT2, and RM3 are located in the orange zone (high risk) of the risk matrix. According to [68], cap and trade schemes are schemes in which companies can trade their emissions (Rreg1) through certain established caps, which are more common in multinational companies. However, this can result in a high price for tradable emission permits, leading to higher operating costs, asset impairment, and early retirement of existing assets due to this change in regulation.

In relation to the Rreg4 risk, it is important to note that in Colombia the Superintendency of Finance issued External Circular 031, which regulates and encourages the disclosure of information on social, environmental, and climate issues, under a financial materiality perspective. This regulation applies to companies listed on the Colombian Stock Exchange (BVC), that is, publicly traded companies.

However, this requirement for companies to report the amount of GHG emissions they produce and to determine whether they are in compliance with general regulations or whether they are exceeding permitted GHG emission generation, may increase credit risk for banks and entities that do business with these companies. In addition, the information disclosed allows investors to make informed decisions about whether or not to invest in companies with certain levels of emissions.

However, the technological progress of renewable energy and energy efficiency processes (RT2), which consists of new technological developments that allow companies to achieve better results in their energy processes, will also generate direct transition costs with respect to renewable energy, as well as higher operating costs.

In the context of stakeholder concerns about climate change (RM3), this type of risk could lead to investment aversion, resulting in losses on investments in companies, leading to losses; as investors' awareness and expectations about climate change are increasing, they incorporate climate risk considerations into their investment decisions. Therefore, further research on the impact of corporate sentiment on climate change would help to improve our understanding of this transmission channel. Another impact that may be caused by climate change concerns is an increase in counterparty litigation, which generates other risks, such as reputational risks on certain environmental issues, which ultimately leads to increased costs, and thus, to reduced investment in unsustainable assets.

However, it is very important for companies to pay attention to changes in the environment, regardless of the risk typology, taking into account that the risks RM1, RM4, Rrep1, Rrep2, Rrep3, and Rrep4, have a medium risk rating, as the latter risks, which are related to the feelings and expectations of individuals and companies, are the least investigated.

6. Conclusions and Future Work

It is important to note that the MCDM methods are based on different principles and algorithms, since each was designed to solve specific problems. Some techniques weight the criteria differently, which can lead to different results for the same dataset. On the other hand, if the data used are not at a similar level of analysis, it can distort the comparison. This may require the use of standardisation or normalisation techniques.

However, even if two MCDM techniques have a high correlation, it does not mean that one method influences the other; both could be influenced by external factors. It is important to note that correlation does not imply causation. Each method was designed for different problems or contexts, so it is important to understand the weaknesses and strengths of each method and to verify that the method is appropriate for the problem being addressed in each investigation. Therefore, there is no one method that is more appropriate than another.

When comparing the results obtained by the MCDM and fuzzy logic techniques, it is possible to determine that RM2 and Reg2 are the most serious risks according to the results. Nevertheless, the advantage of using methods such as fuzzy logic is not only the ability to generate a ranking of options, in this case, risks, but also to classify them into different risk levels, as was intended in this research.

The use of fuzzy logic, in combination with other decision-making techniques, can bring clarity and precision to the detailed study of the climate transition risks. The advantage of using fuzzy logic instead of other traditional qualitative approaches is the ability to transform vague and analogous information into unambiguous data that can be used to make informed and unambiguous decisions on various issues, such as climate transition risk management.

It can be concluded that technological risks are the most significant, followed by regulatory and market risks, for the economic sector analysed. Notably:

- All risks evaluated have a medium-to-high impact.
- The technological risks are particularly notable because of their high probability of occurrence and their considerable impact.
- The risks RT1, RT2, and RT3 have a significant probability of occurrence and high impact, which makes them particularly critical.
- Market and regulatory risks are the most significant in terms of risk management. In particular, RM2 is the most probable and has the most significant impact.
- Raw material price fluctuations are a common occurrence in the manufacturing sector, but are difficult to anticipate due to their unpredictable nature.
- Reputational risks, although located in the lower right quadrant of the matrix, can have a significant impact and are not as widely studied by experts. Although their probability of occurrence is low, they can still have a significant impact, so it is essential to keep them under control.

From the above findings and analysis, it can be established that technological risks related to climate change are currently the most important for organisations in this sector, followed by regulatory and market risks, which are the key drivers for organisations at the financial level.

With this in mind, it is important to stress that:

- Climate regulations vigorously aim to internalise carbon externalities, positioning them as a crucial driver of risk management. This is frequently achieved through powerful incentive-based regulations, such as the impactful implementation of carbon pricing mechanisms. The advent of groundbreaking technological advancements significantly reduces costs, a phenomenon often stimulated by pioneering climate regulations, thereby making low-carbon technologies more affordable than ever.
- Consumer and market preferences will drive demand and prices. Given this demand–pull effect, market preferences can influence the pace of technology adoption and

policy development, demonstrating the strong interaction between these three drivers of climate change.

- It is essential for companies to pay attention to changes in the environment, regardless of the type of risk, taking into account that the risks RM1, RM4, Rrep1, Rrep2, Rrep3, and Rrep4 have a medium risk rating. This is because the latter risks, which relate to the feelings and expectations of individuals and companies, are the least researched.

Therefore, efforts to better address and manage climate change are expected to drive technological innovations that will enable the transition to low-carbon economies. This could make the most polluting technologies relatively more expensive if carbon taxes or other stricter regulations are introduced, as companies that rely on carbon-intensive technologies could become less competitive if they do not adopt new technologies.

Some results presented in this study may differ from other analyses of climate transition risk assessment, taking into account that the experts assessed in this study belong to a company in the economic sector analysed, and thus, know the reality of the company and have knowledge associated with the risks, which is important in determining how exposed the company may be to this type of climate risk.

The severity of the threat that can affect an organisation depends on its vulnerability and resilience. Furthermore, the economic impact is the result of the interaction between exposure, vulnerability, and resilience. Therefore, an assessment of the financial consequences of climate transition risks seeks to quantify the economic impact on the underlying unit of analysis.

However, companies are expected to create a culture of identifying, assessing, and managing climate transition risks through this type of analytical tool. It should be noted that this tool can be used not only for the identification of purely climatic risks, but also for any type of traditional or emerging risk faced by companies, as well as climate physical risks.

This research aimed to identify climate transition risks that could affect organisations that belong to the processed food sector. It is important to note that these specific risks were identified for a specific company, taking into account its context and realities. Exposure to a particular type of risk will depend largely on the sector and type of industry. Many risks can be added to this matrix as necessary for the analysis given the needs and specificities of each organisation.

The consequences of our findings for decision making are substantial. The key risks identified, including price fluctuations and the availability of raw materials, require specific mitigation and adaptation strategies from the organisations. For example, companies should consider investing in less carbon-intensive technologies and preparing for potential increases in carbon taxes. In addition, it is crucial to acknowledge the limitations of our study, such as the dependence on historical data and the subjectivity of expert evaluations. Future research could investigate the incorporation of real-time data and the application of advanced artificial intelligence techniques to improve the precision and relevance of risk assessments.

We present a methodology that uses a combination of known techniques in risk environments and that returns a matrix with information that is easy to handle and interpret for the organisation's employees. The disadvantage is that, although it is a methodology that can be easily adapted, it needs to be adapted to each organisation according to its internal characteristics, so it needs experts within the organisation to be able to run the TOPSIS model again and establish weights according to each organisation.

It is suggested that future research should focus on methods that can weigh vulnerability, exposure, and resilience on the same impact criterion as input variables for the fuzzy logic model. This would allow experts to capture more information, similar to the MCDM model, since the literature suggests that there is a relationship between these four criteria.

However, it is suggested that for the application of this methodology in specific companies, a representative sample of the different areas of the organisation should be used, as it is important that all areas, without exception, are involved in the risk assessment and subsequent evaluation process; considering as experts people with knowledge associated with the risks to which the business may be exposed.

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References

1. Brönnimann, S.; Martius, O.; Rohr, C.; Bresch, D.N.; Lin, K.H.E. Historical weather data for climate risk assessment. *Ann. N. Y. Acad. Sci.* **2019**, *1436* , 14. [CrossRef]
2. Hanski, J.; Keränen, J.; Molarius, R. Tools and Methods for Supporting Regional Decision-Making in Relation to Climate Risks. In *Climate Change and Global Warming*; IntechOpen: London, UK, 2019.
3. Huang, H.H.; Kerstein, J.; Wang, C. The impact of climate risk on firm performance and financing choices: An international comparison. *J. Int. Bus. Stud.* **2018**, *49*, 633–656. [CrossRef]
4. Sakhel, A. Corporate climate risk management: Are European companies prepared? *J. Clean. Prod.* **2017**, *165*, 103–118. [CrossRef]
5. Oguntuase, O.J. Climate Change, Credit Risk and Financial Stability. In *Banking and Finance*; IntechOpen: London, UK, 2020.
6. Kalra, N.; Hallegatte, S.; Lempert, R.; Brown, C.; Fozzard, A.; Gill, S.; Shah, A. Agreeing on Robust Decisions: New Processes for Decision Making under Deep Uncertainty. In *World Bank Policy Research Working Paper*; No. 6906; The World Bank: Washington, DC, USA, 2016.
7. Heal, G.; Millner, A. Uncertainty and Decision in Climate Change Economics. *Natl. Bur. Econ. Res.* **2013**, 1–24. [CrossRef]
8. Bank for International Settlements. Climate-Related Financial Risks—Measurement Methodologies. 2021. Available online: https://www.bis.org/bcbs/publ/d518.pdf (accessed on 18 December 2023).
9. Markowski, A.S.; Mannan, M.S. Fuzzy risk matrix. *J. Hazard. Mater.* **2008**, *159*, 152–157. [CrossRef] [PubMed]
10. Shapiro, A.F.; Koissi, M.C. Risk assessment applications of fuzzy logic. *Casualty Actuar. Soc. Can. Inst. Actuar. Soc. Actuar.* **2015**, *390*, 1–112.
11. Pena, A.; Patino, A.; Chiclana, F.; Caraffini, F.; Gongora, M.; Gonzalez-Ruiz, J.D.; Duque-Grisales, E. Fuzzy convolutional deep-learning model to estimate the operational risk capital using multi-source risk events. *Appl. Soft Comput.* **2021**, *107*, 107381. [CrossRef]
12. Peña, A.; Puerta, A.; Bonet, I.; Caraffini, F.; Gongora, M.; Ochoa, I. A Multispectral Image Classification Framework for Estimating the Operational Risk of Lethal Wilt in Oil Palm Crops. In Proceedings of the International Conference on the Applications of Evolutionary Computation (Part of EvoStar), Aberystwyth, UK, 3–5 March 2023; Springer: Berlin/Heidelberg, Germany, 2023; pp. 491–506.
13. Bacanli, U.G.; Firat, M.; Dikbas, F. Creating proactive behavior for the risk assessment by considering expert evaluation: A case of textile manufacturing plant. *Complex Intell. Syst.* **2021**, *7*, 941–959. [CrossRef]
14. Djenadic, S.; Tanasijevic, M.; Jovancic, P.; Ignjatovic, D.; Petrovic, D.; Bugaric, U. Risk Evaluation: Brief Review and Innovation Model Based on Fuzzy Logic and MCDM. *Mathematics* **2022**, *10*, 811. [CrossRef]
15. Ak, F.M.; Gul, M. AHP–TOPSIS integration extended with Pythagorean fuzzy sets for information security risk analysis. *Complex Intell. Syst.* **2019**, *5*, 113–126. [CrossRef]
16. Hajiaghaei-Keshteli, M.; Cenk, Z.; Erdebilli, B.; Özdemir, Y.S.; Gholian-Jouybari, F. Pythagorean Fuzzy TOPSIS Method for Green Supplier Selection in the Food Industry. *Expert Syst. Appl.* **2023**, *223*, 120036. [CrossRef]
17. Beiranvand, B.; Rajaee, T. Environmental Risk Management of Eyvashan Dam Using Traditional-FMEA and FIS-FMEA Methods. *J. Soft Comput. Civ. Eng.* **2023**, *7*, 1–20. [CrossRef]
18. En-Naaoui, A.; Kaicer, M.; Aguezzoul, A. A novel decision support system for proactive risk management in healthcare based on fuzzy inference, neural network and support vector machine. *Int. J. Med Inform.* **2024**, *186*, 105442. [CrossRef] [PubMed]
19. Mukherjee, S.; De, A.; Roy, S. Supply chain risk prioritization: A multi-criteria based Intuitionistic Fuzzy TOPSIS approach. *Int. J. Qual. Reliab. Manag.* **2024**, *41*, 1693–1725. [CrossRef]
20. Yang, X. Financial Risk Assessment Model Based on Fuzzy Logic. *J. Electr. Syst.* **2024**, *20*, 192–205. [CrossRef]

21. Yazo-Cabuya, E.J.; Ibeas, A.; Herrera-Cuartas, J.A. Integration of Sustainability in Risk Management and Operational Excellence through the VIKOR Method Considering Comparisons between Multi-Criteria Decision-Making Methods. *Sustainability* **2024**, *16*, 4585. [CrossRef]
22. Reicyzadeh, Z.; Ashofteh, P.S.; Golfam, P. Risk analysis under different mitigation strategies for potential threats in wastewater treatment systems. *Environ. Dev. Sustain.* **2024**, 1–30. [CrossRef]
23. Ak, M.F. *A Neuro-Fuzzy-Based Multi-Criteria Risk Evaluation Approach: A Case Study of Underground Mining*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 67–205. [CrossRef]
24. Nabipour, N.; Mosavi, A.; Hajnal, E.; Nadai, L.; Shamshirband, S.; Chau, K.W. Modeling Climate Change Impact on Wind Power Resources Using Adaptive Neuro-Fuzzy Inference System. *Eng. Appl. Comput. Fluid Mech.* **2020**, *14*, 491–506. [CrossRef]
25. Gocić, M.; Motamedi, S.; Shamshirband, S.; Petković, D.; Hashim, R. Potential of adaptive neuro-fuzzy inference system for evaluation of drought indices. *Stoch. Environ. Res. Risk Assess.* **2015**, *29*, 1993–2002. [CrossRef]
26. Bacanli, U.G.; Firat, M.; Dikbas, F. Adaptive Neuro-Fuzzy Inference System for drought forecasting. *Stoch. Environ. Res. Risk Assess.* **2009**, *23*, 1143–1154. [CrossRef]
27. Aydin, M.; Akyuz, E.; Turan, O.; Arslan, O. Validation of risk analysis for ship collision in narrow waters by using fuzzy Bayesian networks approach. *Ocean Eng.* **2021**, *231*, 108973. [CrossRef]
28. Senol, Y.E.; Yasli, F. A risk analysis study for chemical cargo tank cleaning process using Fuzzy Bayesian Network. *Ocean Eng.* **2021**, *235*, 1–20. [CrossRef]
29. Senol, Y.E.; Yasli, F. Fuzzy approach and possibility to solve uncertainty weaknesses in conventional quantitative risk assessment. *Soft Comput.* **2023**, *27*, 6109–6133. [CrossRef]
30. Abed, H.R.; Rashid, H. A New Risk Assessment Model for Construction Projects by Adopting a Best–Worst Method–Fuzzy Rule-Based System Coupled with a 3D Risk Matrix. *Iran. J. Sci. Technol. Trans. Civ. Eng.* **2023**, *48*, 541–559. [CrossRef]
31. Biswas, T.K.; Zaman, K. A Fuzzy-Based Risk Assessment Methodology for Construction Projects under Epistemic Uncertainty. *Int. J. Fuzzy Syst.* **2019**, *21*, 1221–1240. [CrossRef]
32. Chaher, Z.C.; Soomro, A.R. Risk Analysis Model for Construction Projects Using Fuzzy Logic. *Int. J. Adv. Res. Eng.* **2016**, *3*, 17.
33. Tripathy, D.P.; Ala, C.K. Risk Assessment in Underground Coalmines Using Fuzzy Logic in the Presence of Uncertainty. *J. Inst. Eng. (India) Ser. D* **2018**, *99*, 57–163. [CrossRef]
34. Aliyev, E.A.; Gabibov, I.A.; Ismailova, R.A.; Huseynov, R.O. Application of fuzzy logic for risk assessment of investment projects. *SOCAR Proc.* **2022**, *140*, 026–032. [CrossRef]
35. Casalino, G.; Grassi, R.; Iannotta, M.; Pasquadibisceglie, V.; Zaza, G. A Hierarchical Fuzzy System for Risk Assessment of Cardiovascular Disease. In Proceedings of the 2020 IEEE Conference on Evolving and Adaptive Intelligent Systems (EAIS), Bari, Italy, 27–29 May 2020; pp. 1–7. [CrossRef]
36. Studenikin, D.E.; Chizhikova, M.I. The onboard expert measuring system for assessing the technogenic risk during towing operations based on the fuzzy logic. *J. Phys. Conf. Ser.* **2021**, *2061*. [CrossRef]
37. Vahdani, B.; Salimi, M.; Charkhchian, M. A new FMEA method by integrating fuzzy belief structure and TOPSIS to improve risk evaluation process. *Int. J. Adv. Manuf. Technol.* **2015**, *77*, 357–368. [CrossRef]
38. Gallab, M.; Bouloiz, H.; Alaoui, Y.L.; Tkiouat, M. Risk Assessment of Maintenance activities using Fuzzy Logic. *Int. J. Adv. Manuf. Technol.* **2019**, *148*, 226–235. [CrossRef]
39. Seker, S. A new model for risk assessment in glass manufacturing using Risk Matrix based IVIF-TOPSIS method. *J. Intell. Fuzzy Syst.* **2021**, *42*, 541–550. [CrossRef]
40. Rani, M.P.; Aremu, B.; Fernando, X. *Forecasting Flash Floods with Optimized Adaptive Neuro-Fuzzy Inference System and Internet of Things*; Springer: Berlin/Heidelberg, Germany, 2023; pp. 23–38. [CrossRef]
41. Katipoğlu, O.M. Prediction of missing temperature data using different machine learning methods. *Arab. J. Geosci.* **2022**, *15*, 21. [CrossRef]
42. Zamelina, A.J.F.; Adytia, D.; Ramadhan, A.W. Forecasting of Maximum Temperature by using ANFIS and GRU Algorithms: Case Study in Jakarta, Indonesia. In Proceedings of the 2022 10th International Conference on Information and Communication Technology (ICoICT), Virtual Conference, 2–3 August 2022; pp. 222–227. [CrossRef]
43. Aydin, F.; Gümüş, B. Comparative analysis of multi-criteria decision making methods for the assessment of optimal SVC location. *Power Syst. Power Electron.* **2022**, *70*, 1–11. [CrossRef]
44. Ceballos, B.; Lamata, M.; Pelta, D. CA comparative analysis of multi-criteria decision-making methods. *Power Syst. Power Electron.* **2016**, *5*, 315–322. [CrossRef]
45. Wu, W.; Kou, G.; Peng, Y. Group decision-making using improved multi-criteria decision making methods for credit risk analysis. *Filomat* **2016**, *30*, 4135–4150. [CrossRef]
46. Zavadskas, E.; Kaklauskas, A.; Vilutiene, T. Multicriteria evaluation of apartment blocks maintenance contractors: Lithuanian case study. *Int. J. Strateg. Prop. Manag.* **2009**, *13*, 319–338. [CrossRef]
47. Yücenur, G.N.; Çaylak, Ş.; Gönül, G.; Postalcıoğlu, M. An integrated solution with SWARA&COPRAS methods in renewable energy production: City selection for biogas facility. *Renew. Energy* **2020**, *145*, 2587–2597. [CrossRef]
48. Topcu, I.; Ulengin, F.; Kabak, O.; Isik, M.; Unver, B.; Ekici, S.O. The evaluation of electricity generation resources: The case of Turkey. *Energy* **2019**, *167*, 417–427. [CrossRef]

49. Dhurkari, R.K. MCDM Methods: Practical difficulties and future directions for improvement. *Rairo Oper. Res.* **2022**, *56*, 2221–2233. [CrossRef]
50. Odu, G. Weighting methods for multi-criteria decision making technique. *J. Appl. Sci. Environ. Manag.* **2019**, *23*, 1449–1457. [CrossRef]
51. Jafaryeganeh, H.; Ventura, M.; Soares, C.G. Application of multi-criteria decision making methods for selection of ship internal layout design from a Pareto optimal set. *Ocean. Eng.* **2020**, *202*, 107151. [CrossRef]
52. Paradowski, B.; Szyjewski, Z. Comparative analyses of multi-criteria methods in supplier selection problem. *Procedia Comput. Sci.* **2022**, *207*, 4593–4602. [CrossRef]
53. de Vries, T. Configurator Type Selection Improvement through Multi Criteria Decision Making. Master's Thesis, University of Twente, Enschede, The Netherlands, 2020.
54. Ghorabaee, M.K.; Zavadskas, E.K.; Turskis, Z.; Antucheviciene, J. A New Combinative Distance-Based Assessment(Codas) Method For Multi-Criteria Decision-Making. *Econ. Cybern. Stud. Res.* **2016**, *50*, 25–44.
55. Zaky, M. Risk Analysis using Fuzzy System based Risk Matrix Methodology. *Arab J. Nucl. Sci. Appl.* **2018**, *51*, 204–212. [CrossRef]
56. Abdelkader, E.M.; Zayed, T.; Fathali, H.E.; Alfalah, G.; Al-Sakkaf, A.; Moselhi, O. An Integrated Multi-Criteria Decision Making Model for the Assessment of Public Private Partnerships in Transportation Projects. *Mathematics* **2023**, *11*, 3559. [CrossRef]
57. Pérez-Pérez, J.F.; Gómez, P.I.; Bonet, I.; Sánchez Pinzón, M.S.; Caraffini, F.; Lochmuller, L. Validation of Variables Related to Climate Transition Risk—Data Collection Form. 2023. Available online: https://forms.gle/SaK2XQoo3tFCvyq16 (accessed on 1 June 2024).
58. Bingler, J.A.; Colesanti Senni, C. Taming the Green Swan: How to improve climate-related financial risk assessments. *CER-ETH—Cent. Econ. Res. ETH Zur.* **2020**, *80*, 156. [CrossRef]
59. Pachauri, R.K.; Allen, M.R.; Barros, V.R.; Broome, J.; Cramer, W.; Christ, R.; Church, J.A.; Clarke, L.; Dahe, Q.; Dasgupta, P.; et al. *Climate Change 2014: Synthesis Report; Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*; IPCC: Paris, France, 2014.
60. Ulfah, M.; Ferdinant, P.F.; Trenggonowati, D.L.; Salsabila, M. Supply-chain risk mitigation with integration of House of Risk and fuzzy logic: A case study in bakery industry. *J. Ind. Serv.* **2022**, *8*, 151–157. [CrossRef]
61. Cestero, E.V. Un Enfoque Borroso Para el Análisis y la Gestión de Riesgos en Sistemas de Información. Ph.D. Thesis, Universidad Politénica de Madrid, Madrid, Spain, 2013.
62. Fakhravar, H. Quantifying Uncertainty in Risk Assessment using Fuzzy Theory. *arXiv* **2020**, arXiv:2009.09334.
63. Tien, D.H.; Trung, D.D.; Thien, N.V. Comparison of multi-criteria decision making methods using the same data standardization method. *J. Mech. Eng.* **2022**, *72*, 57–72.
64. Fu, Y.K.; Wu, C.J.; Liao, C.N. Selection of In-Flight Duty-Free Product Suppliers Using a Combination Fuzzy AHP, Fuzzy ARAS, and MSGP Methods. *Math. Probl. Eng.* **2021**, *2021*, 144–155. [CrossRef]
65. Khodadadi-Karimvand, M.; Shirouyehzad, H. Well Drilling Fuzzy Risk Assessment Using Fuzzy FMEA and Fuzzy TOPSIS. *J. Fuzzy Ext. Appl.* **2021**, *2*, 144–155. [CrossRef]
66. Kölbel, J.; Leippold, M.; Rillaerts, J.; Wang, Q. Does the CDS Market Reflect Regulatory Climate Risk Disclosures? *SSRN Electron. J.* **2021**. [CrossRef]
67. European Systemic Risk Board. Climate-Related Risk and Financial Stability. 2021. Available online: https://www.esrb.europa.eu/pub/pdf/reports/esrb.climateriskfinancialstability202107~79c10eba1a.en.pdf?71a273dc36a85ef05c8bed530466f900 (accessed on 1 June 2024).
68. Gasbarro, F.; Iraldo, F.; Daddi, T. The drivers of multinational enterprises' climate change strategies: A quantitative study on climate-related risks and opportunities. *J. Clean. Prod.* **2017**, *160*, 8–26. [CrossRef]