

A combined multi-criteria risk decision and rank aggregation approach with multiple risk factors with an application to greenhouse gas emission risk assessment of sectors

Irene Brito

Department of Mathematics, Centre of Mathematics, University of Minho, 4800-045 Guimarães, Portugal.

Contributing authors: ireneb@math.uminho.pt;

Abstract

In this work, a combined multi-criteria risk decision making and rank aggregation method, WASPAS-WBR, is proposed for the risk assessment of alternatives according to different risk factors. The method consists first in applying the weighted aggregated sum product assessment (WASPAS) method, with criteria defined by risk measures, in order to obtain a ranking of the alternatives for a given risk factor. After obtaining the rankings for the different risk factors, the rank aggregation method weighted Borda ranking (WBR) is applied to establish a final ranking of the alternatives. The WASPAS-WBR method is illustrated with an application to the risk analysis of greenhouse gas emission by sectors, considering the risk factors carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O). The aim is to classify the sectors in terms of risk for greenhouse gas emission, first by evaluating the sectors according to each individual air pollutant using the WASPAS method with risk criteria mean, value at risk and tail value at risk, and then by assessing the combined risk with the WASPAS-WBR method. Data corresponding to annual greenhouse gas concentrations measured in Portugal in the time horizon from 1990 to 2022 are analysed.

Keywords: risk assessment, risk measures, multi-criteria decision making, ranking aggregation, greenhouse gas emission

1 Introduction

Multi-criteria decision-making (MCDM) methods are decision support systems that permit making decisions under different criteria, by evaluating and ranking the alternatives with respect to the different criteria (see e.g. [1],[2],[3]). The weighted aggregated sum product assessment (WASPAS) method is one of these methods, that combines the well known weighted sum model and weighted product model (see [4], [5], [6] and the review in [7]).

In the present work, the WASPAS method will be adapted to the risk assessment of alternatives by defining risk criteria using different risk measures and additionally evaluating the alternatives according to different risk factors. This is achieved by combining the WASPAS method with the rank aggregation method weighted Borda ranking (see [8], [9], [10] and references therein) in the following way. The output rankings of the alternatives that are obtained by applying the WASPAS method for the different risk factors are aggregated using the weighted Borda ranking (WBR) to get a final ranking of alternatives. The resulting combined WASPAS-WBR method can be applied to risk assessment problems in different contexts and it will be here illustrated through an application to the risk assessment of greenhouse gas emission by sectors.

Since greenhouse gases trap heat and are responsible for raising the surface temperature of the earth, contributing to climate change, the reduction of greenhouse gas emissions is essential to slow the rate of global warming and mitigate its impact on environment and human health. In the European Union, the European Climate Law sets a target to reduce the emissions by at least 55% in 2030, compared to 1990 [11]. In order to fulfil these ambitions, risk measurement of greenhouse gases and the identification and risk classification of sectors responsible for the emissions is important for the implementation of appropriate solutions.

This study specifically analyses the emissions of the three most emitted greenhouse gases, CO₂ (carbon dioxide), CH₄ (methane), N₂O (nitrous oxide), in Portugal by different sectors: industrial processes, agriculture, forest and land use change, waste, energy, considering annual data from 1990 to 2022 (emissions in kt of CO₂ equivalent), extracted from the Portuguese Institute of Statistics (INE) [12]. The aim is to classify the sectors based on their greenhouse gas emission risk, both for individual air pollutants and for conjoint pollution.

The analysis will incorporate three different risk measures for establishing the assessment criteria in the WASPAS method, including mean, value at risk, and tail value at risk (see e.g. [13], [14]). Risk measures are essential tools in decision-making because they help quantify potential negative outcomes associated with certain actions or processes (see e.g. [15], [16], [17]). A risk measure associates a real value to a random variable representing a loss. The mean measures the expected outcome. This basic risk measure will then be complemented by the value at risk, a quantile risk measure, that measures a maximal loss for a given probability, and by the tail value at risk, that measures the expected loss, given that the loss exceeds the value at risk. Value at risk and tail value at risk are standard risk measure in actuarial risk theory to assess the exposure to risk (see [14], [18]). However, these risk measures are also relevant and can be well adapted to environmental risk assessment. In the present study, the mean gives

a general indication of the air pollutant concentration. The value at risk identifies a maximal pollutant concentration that can be reached with a high probability and the tail value at risk informs about the expected exceedance concentration of the value at risk.

In practice, the WASPAS-WBR method applied to the risk assessment problem consists first in calculating the risk measures for each risk factor, i.e. for the greenhouse gas pollutants CO_2 , CH_4 and N_2O , emitted by the five sectors (alternatives): industrial processes, agriculture, forest and land use change, waste, energy, based on the empirical distribution. In the first phase, the WASPAS method is then initiated with the calculated risk values and it leads to three rankings of alternatives (one ranking corresponding to each greenhouse gas). In the second phase, the output rankings are then aggregated with the WBR method to establish the final risk classification of sectors.

Examples of works addressing greenhouse gas emissions and their associated risks include the study in [19], which examines greenhouse gas emissions in Brazilian agriculture and livestock sectors and the risk to Amazonia conservation using environmental networks. Kumar and Sharma [20] predict the vulnerability of hydropower reservoir in India to greenhouse gas emissions using a risk assessment tool, where the prediction of CO_2 and CH_4 fluxes are based on input data calculated from mean annual temperature, rainfall, runoff, and age of the reservoir. Ho et al. [21] proposed data-driven models to qualitatively assess the risks of greenhouse gas accumulation in an urban river system in Ecuador. Boubaker et al. [22] analysed CO_2 emissions and environmental risks, demonstrating long-term challenges posed by the unchanged trend of global CO_2 emissions and, using numerical methods, determining a reduction rate in global emissions to achieve a goal of limiting warming. Also information on the order of CO_2 emissions recovery for different sectors were provided. Akcan [23] present a hybrid multi criteria decision making method that consists of Analytic Hierarchy Process and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for determining the risk priority of the sources of greenhouse gas emissions in Turkey (based on CO_2 , CH_4 and N_2O data).

In the previously mentioned works, risk is described using total emission values or mean (or average) emission rates of greenhouse gases, usually considering separately a specific pollutant. In [23], the MCDM method TOPSIS is used to combine emission values of three air pollutants. In that approach the criteria are thus the air pollutants, however also only emission values are considered. The novelty of the here presented work, compared to the previously mentioned studies, is that risk is assessed using three different risk measures, mean, value at risk and tail value at risk, where in the MCDM method the criteria are now risk measures and which are computed from the emission data distribution. Thus, this work extends the description based on the mean taking additionally into account the information about the tail of the data distribution, that may be relevant for extreme value detection (e.g. very high pollutant emissions). Also the combination of the resulting risk rankings for the three risk factors with weights determined quantitatively based on the data sample is new, permitting a multiple risk factor assessment.

The rest of the paper is structured as follows. In Section 2, basic concepts of risk measurement are explained, including the definitions of the risk measures used for the risk assessment process. Section 3 contains the description of the combined multi-criteria decision making and rank aggregation methodology, called WASPAS-WBR. In Section 4, the proposed methodology is applied to the risk assessment of sectors for greenhouse gas emission. The conclusion is presented in Section 5.

2 Risk measurement

Measuring risk is an important aspect of decision-making in many contexts. In risk assessment problems the aim is to quantify the risk of different alternatives using risk measures. This enables a final classification or ordering of alternatives, allowing for more informed and appropriate risk-based decisions. The basic principles of risk measurement required for the here considered analysis are presented as follows.

Let $\mathcal{A}$ be a set of alternatives consisting of elements that a decision maker can analyse. It is assumed that a binary risk order relation exists on $\mathcal{A}$ that describes the risk ordering.

Definition 1 Let $\mathcal{A}$ be a set of alternatives and consider $A, B \in \mathcal{A}$. The binary risk order relation, defined on $\mathcal{A}$ and denoted by $\preceq$, represents the risk ordering, where $A \preceq B$ means that B is at least as risky as A . The risk order relation is a weak order relation, characterized by the following axioms:

- (a) reflexive: $\forall A \in \mathcal{A} : A \preceq A$;
- (a) complete: $\forall A, B \in \mathcal{A} : A \preceq B \vee B \preceq A$;
- (b) transitive: $\forall A, B, C \in \mathcal{A} : A \preceq B \wedge B \preceq C \Rightarrow A \preceq C$.

The risk indifference relation $\sim$ is defined by

$$A \sim B \Leftrightarrow A \preceq B \wedge B \preceq A,$$

meaning that A and B are indifferent, and the strict risk relation $\prec$, by

$$A \prec B \Leftrightarrow A \preceq B \wedge \neg(A \sim B),$$

meaning that B is (strictly) riskier than A .

It is further assumed that the risk associated with each alternative is characterized by a random variable. Consider that X_A and X_B are risk random variables corresponding to the alternatives A and B , respectively. A risk measure quantifies risk, is associated with the risk order relation and permits deciding between alternatives in a numerical way as follows.

Definition 2 Let $\mathbb{X}$ be a set of risk random variables and let $X_A, X_B \in \mathbb{X}$. A risk measure $R : \mathbb{X} \rightarrow \mathbb{R}$ is a mapping from the set of risk random variables to the set of real numbers that represents numerically the risk ordering:

$$A \preceq B \Leftrightarrow R(X_A) \leq R(X_B),$$

meaning that B is at least as risky as A if and only if the risk of X_B is at least as high as the risk of X_A quantified with the risk measure R .

In this work, the following three risk measures, denoted by R_1 , R_2 and R_3 , are employed, where, given a risk random variable $X \in \mathbb{X}$, it is assumed that higher outcomes of X imply a higher risk (this is compatible with the risk perception in cases where X represents the concentration of a greenhouse gas pollutant).

1. Expected value:

The expected value, or mean,

$$R_1(X) := \mathbb{E}(X)$$

measures the average risk. A higher expected value indicates a higher risk.

2. Value at risk (VaR):

The VaR at the confidence level α , $0 < \alpha < 1$, is the quantity π_α defined by

$$R_2(X) := \text{VaR}_\alpha(X) = \inf\{\pi_\alpha \in \mathbb{R} : P(X \leq \pi_\alpha) \geq \alpha\}.$$

Here, the 95%-quantile, $\pi_{0.95}$, satisfying $P(X \leq \pi_{0.95}) \geq 0.95$, will be used. A higher VaR indicates a higher risk.

3. Tail value at risk (TVaR):

The tail value at risk, or conditional tail expectation, is defined by

$$R_3(X) := \text{TVaR}_\alpha(X) = \mathbb{E}(X|X > \pi_\alpha),$$

where π_α is the value at risk at the confidence level $\alpha = 0.95$. A higher TVaR indicates a higher risk.

3 WASPAS–WBR method for risk assessment with multiple risk factors

The here proposed combined multi-criteria decision making and rank aggregation approach, WASPAS-WBR, for risk assessment with multiple factors consists of two phases. In the first phase, the MCDM method Weighted Aggregated Sum Product Assessment (WASPAS) is used to evaluate the risk of each alternative based on various risk factors. The resulting risk rankings of the alternatives then serve as inputs for the rank aggregation process in the second phase. In that phase, the weighted Borda ranking (WBR) method is applied to determine the final risk ranking. The methodology, illustrated in Figure 1 for each phase will be described in more detail in the next paragraphs.

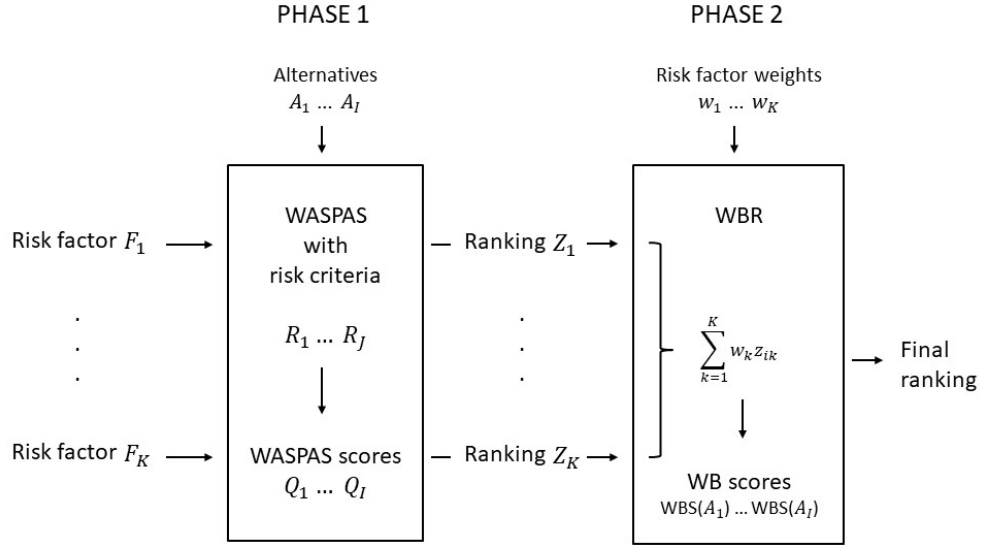


Fig. 1 Overview of WASPAS-WBR methodology.

Phase 1: MCDM method – Weighted Aggregated Sum Product Assessment

In multi-criteria decision-making, the Weighted Aggregated Sum Product Assessment is a method proposed by Zavadskas et al. [4] that combines the weighted product model and the weighted sum model for ranking the alternatives. Thereby different weights (subjective or objective) can be assigned to the criteria.

The WASPAS method is adapted to the risk assessment by defining the criteria through risk measures in the following way. Consider a set of alternatives A_i , $i = 1, \dots, I$, with associated risk random variables $X_{F_k, i}$, where F_k , $k = 1, \dots, K$, are different risk factors that can be observed or measured (e.g. different pollutants), and consider different risk measures R_j , $j = 1, \dots, J$. Given a certain risk factor, the application of the WASPAS method requires first the development of a decision (or evaluation) matrix.

Step 1 Consider the risk factor F_k and construct the corresponding risk decision matrix $M_{F_k} = [x_{ij}]_{I \times J}$ given by

$$M_{F_k} = \begin{matrix} & R_1 & R_2 & \cdots & R_J \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_I \end{matrix} & \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1J} \\ x_{21} & x_{22} & \cdots & x_{2J} \\ \vdots & \vdots & \ddots & \vdots \\ x_{I1} & x_{I2} & \cdots & x_{IJ} \end{pmatrix} \end{matrix}, \quad (1)$$

where x_{ij} is the risk value of the alternative A_i determined with the risk measure R_j for the risk factor F_k based on $X_{F_k, i}$, i.e. $x_{ij} = R_j(X_{F_k, i})$.

Step 2 Calculate the normalized risk decision matrix $R = [r_{ij}]_{I \times J}$ using the min-max normalization

$$r_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}, \quad (2)$$

$i = 1, \dots, I, \quad j = 1, \dots, J.$

Step 3 Compute the weighted sum, WS_i , and the weighted product, WP_i , by

$$WS_i = \sum_{j=1}^J w_j r_{ij}, \quad (3)$$

$$WP_i = \prod_{j=1}^J (r_{ij})^{w_j}, \quad i = 1, \dots, I, \quad (4)$$

where w_j are the criteria weights satisfying $\sum_{j=1}^J w_j = 1$.

Step 4 Determine the overall equally weighted aggregated sum product score

$$Q_i = 0.5WS_i + 0.5WP_i, \quad i = 1, \dots, I. \quad (5)$$

Step 5 Rank the alternatives according to their Q_i score, where the alternative with the lowest score is classified as the best ranked alternative and receives the rank order 1.

Step 6 Determine the risk order relation for the alternatives using the following rule. Given two alternatives A_{i_1} and A_{i_2} , $i_1, i_2 \in \{1, \dots, I\}$, then

$$Q_{i_1} < Q_{i_2} \Rightarrow A_{i_1} \prec A_{i_2},$$

meaning that A_{i_2} has a higher risk than A_{i_1} if it has a higher sum product score than A_{i_1} , or, equivalently, if its rank order is superior to that of A_{i_1} .

Remark 1 In Step 2, instead of using the normalization proposed in [4], [6] (normalization by division through the maximum or normalization by division of minimum by the risk values),

here the min-max normalization is used, due to the fact that in the present study the risk values can be negative and positive, as it will be shown. The min-max normalization ensures that (4) is well-defined, even when dealing with negative and positive risk values x_{ij} , since $\min_i x_{ij}$ will be mapped to 0 and $\max_i x_{ij}$ will be mapped to 1. Note that in this work the definition of the normalization is adapted to the risk order relation, maintaining the increasing risk direction in the normalization and in the score in Step 4, where higher normalized values indicate higher risks.

Remark 2 In this work, in Step 4, the mean aggregation of the weighted sum and the weighted product is adopted (see e.g. [24],[25] and references therein). However, also a more general weighted aggregation will be considered. The generalized equation for determining the total relative importance of alternative A_i given by

$$Q_i = \lambda W S_i + (1 - \lambda) W P_i, \quad \lambda = 0, 0.1, \dots, 1, \quad (6)$$

will be used to conduct a sensitivity analysis. When $\lambda = 0$, the WASPAS method reduces to the weighted product model, and when $\lambda = 1$, it reduces to the weighted sum model.

Applying the WASPAS technique to all risk factors F_k , $k = 1, \dots, K$, one gets K rankings for the alternatives.

Phase 2: Rank aggregation method – Weighted Borda Ranking

The second phase consists now in aggregating the rankings obtained for all risk factors in order to determine a final overall risk ranking for the classification of the alternatives. The Borda method (see [8], [9]) is a rank aggregation method based on the ranking positions for each alternative. This method belongs to the batch mode methods, where the aggregated ranking is obtained in one run [26]. Here, a weighted aggregated Borda ranking (see e.g. [10]) is adapted to the risk ranking as follows.

Step 1 Construct the risk ranking matrix $Z = [z_{ik}]_{I \times K}$, containing the K rankings corresponding to the risk factors $F_1, \dots, F_K$ for I alternatives $A_1, \dots, A_I$, given by

$$Z = \begin{matrix} & F_1 & F_2 & \cdots & F_K \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_I \end{matrix} & \begin{pmatrix} z_{11} & z_{12} & \cdots & z_{1K} \\ z_{21} & z_{22} & \cdots & z_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ z_{I1} & z_{I2} & \cdots & z_{IK} \end{pmatrix} \end{matrix},$$

where z_{ik} is the rank order of alternative A_i for the risk factor F_k . The row i of the ranking matrix, represented in vector form by $Z_{I=i} = (z_{i1}, z_{i2}, \dots, z_{iK})$, contains the ranking orders of the alternative A_i obtained with the K risk factors, whereas the column k , $Z_{K=k} = (z_{1k}, z_{2k}, \dots, z_{Ik})$ contains the ranking of the alternatives for the factor F_k .

Step 2 Calculate the weighted Borda score (WBS), or weighted Borda count, for the alternative A_i defined by

$$WBS(A_i) = \sum_{k=1}^K w_k z_{ik}, \quad (7)$$

where the weights associated to the factors F_k satisfy $\sum_{k=1}^K w_k = 1$.

Step 3 Determine the final ranking of the alternatives using the following rule. Given two alternatives A_{i_1} and A_{i_2} , $i_1, i_2 \in \{1, \dots, I\}$, then

$$WBS(A_{i_1}) > WBS(A_{i_2}) \Rightarrow A_{i_1} \succ A_{i_2}, \quad (8)$$

where $i_1, i_2 = 1, \dots, I$. This means that A_{i_1} is riskier than A_{i_2} if A_{i_1} has a higher weighted Borda score than A_{i_2} .

If there is a tie between two alternatives, denoted by $A_{i_1} \sim A_{i_2}$, which happens if there exist two alternatives A_{i_1} and A_{i_2} such that $WBS(A_{i_1}) = WBS(A_{i_2})$, then the tie can be resolved by excluding the lowest grade from each alternative and recalculating the weighted Borda score in Step 2. This process can be repeated iteratively until a strict ordering between the two alternatives is obtained.

The final output of the WASPAS-WBR is the risk ranking of the alternatives obtained with the rule described in Step 3 of Phase 2.

4 Application of the WASPAS-WBR method: greenhouse gas emission risk classification of sectors

This study analyses the emissions of the three most emitted greenhouse gases, CO₂ (carbon dioxide), CH₄ (methane) and N₂O (nitrous oxide) by different sectors in Portugal, using data from 1990 to 2022, extracted from the Portuguese Institute of Statistics (INE) [12]. The data consist of annual averages of the air pollutants CO₂, CH₄ and N₂O (emissions in kt of CO₂ equivalent).

The aim is to apply the combined multi-criteria decision and rank aggregation approach WASPAS-WBR to the risk assessment of sectors based on greenhouse gas emissions. The sectors represent the alternatives. In this study, five sectors are considered (see Table 1).

Table 1 Definitions of the alternatives A_i , $i = 1, \dots, 5$.

A_i	sector
A_1	industrial processes
A_2	agriculture
A_3	forest and land use change
A_4	waste
A_5	energy

The risk factors correspond to the three air pollutants:

$$F_1 - \text{N}_2\text{O}, \quad F_2 - \text{CO}_2, \quad F_3 - \text{CH}_4.$$

Figures 2–4 show the annual amount of greenhouse gas emissions by the different sectors. One can observe in Figure 2 that the sector agriculture contributes the most to N_2O emissions and that the sector industrial processes significantly reduced the emissions from 2010 onwards.

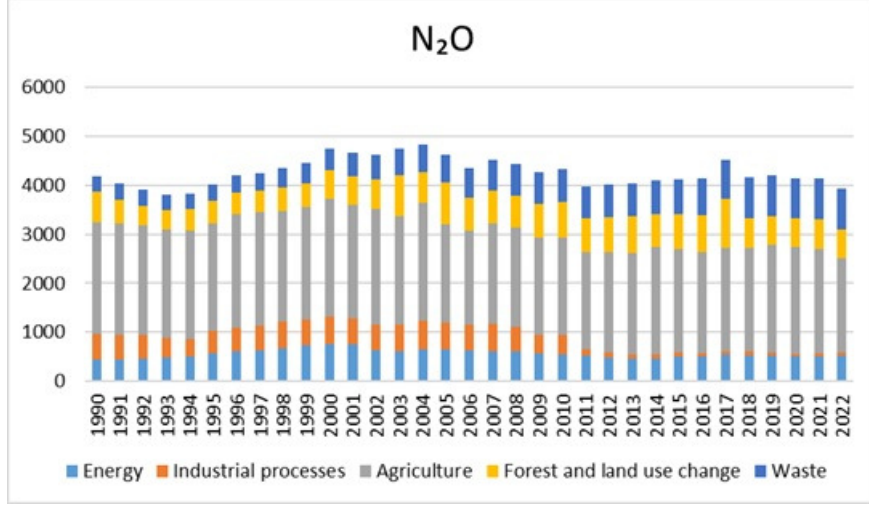


Fig. 2 N_2O emissions by sector (in kt of CO_2 equivalent).

As for the CO_2 emissions, the energy sector contributes with the largest amount to the total emissions (see Figure 3). Note that there are several negative values for the sector forest and land use change, since forests absorb CO_2 from the atmosphere during photosynthesis. Negative values indicate that CO_2 is being removed from the atmosphere rather than emitted. The atypical high (positive) amount of CO_2 recorded in 2017 for the forest and land use change sector can be explained by the fact that in 2017 there were devastating forest fires in Portugal, which had a significant impact on CO_2 emissions in this sector. Note that the forest fires had also an increasing effect on the N_2O value in 2017 in the same sector (see Figure 2), since forest soils tend to emit more N_2O after fire [27]. In general (excluding the year 2017) a decline in total CO_2 emissions can be observed from 2005 onwards, with the last three years showing the lowest emission levels in the entire study period, caused possibly by the pandemic situation.

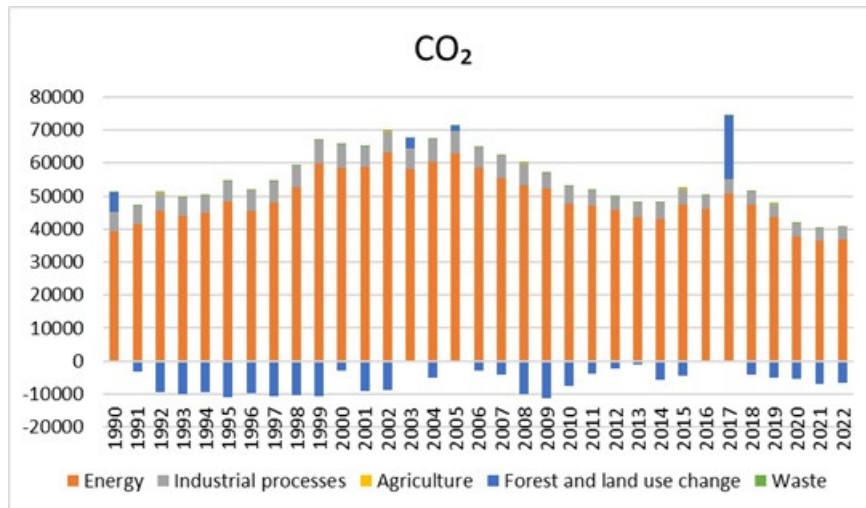


Fig. 3 CO₂ emissions by sector (in kt of CO₂ equivalent).

Regarding the annual emissions of CH₄ by the different sectors, one can identify the sectors waste and agriculture as the largest contributors to the total emissions of this pollutant. The increased emission value in 2017 for the forest and land use change sector can again be attributed to the forest fires that were particularly devastating in that year in Portugal, since fires are a significant source of atmospheric CH₄ (see [28], [29]).

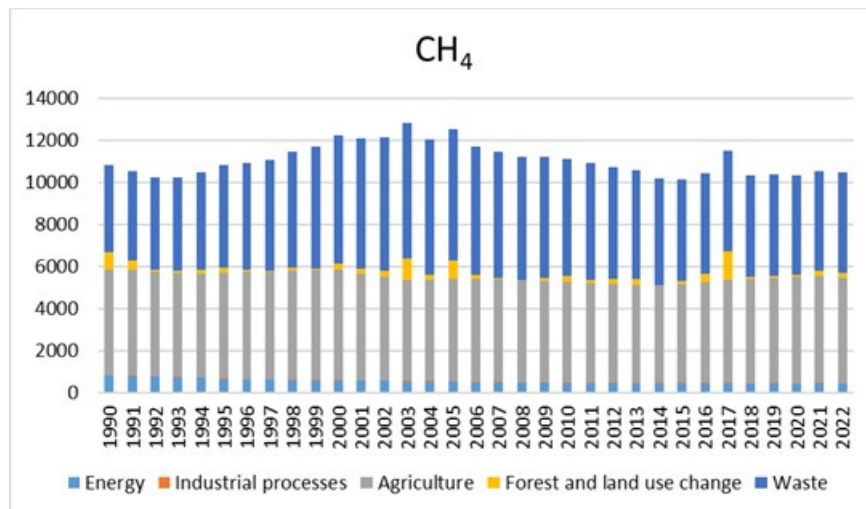


Fig. 4 CH₄ emissions by sector (in kt of CO₂ equivalent).

In order to start with Phase 1 of the WASPAS-WBR method, let X_{CO_2} , X_{CH_4} , $X_{\text{N}_2\text{O}}$ be the random variables representing the emissions of the three air pollutants in kt of CO_2 equivalent. For each alternative (sector) A_i , $i = 1, \dots, 5$, with associated risk random variables $X_{F_k,i}$, $k = 1, 2, 3$, given respectively by $X_{\text{CO}_2,i}$, $X_{\text{CH}_4,i}$, $X_{\text{N}_2\text{O},i}$, the risk measures $R_j(X_{F_k,i})$, $j = 1, 2, 3$, with

- R_1 – mean,
- R_2 – value at risk,
- R_3 – tail value at risk,

were calculated based on the empirical distribution determined for the data samples of CO_2 , CH_4 and N_2O measurements. Thus, the random variables $X_{\text{CO}_2,i}$, $X_{\text{CH}_4,i}$, $X_{\text{N}_2\text{O},i}$ represent the emissions of the pollutants (in kt of CO_2 equivalent) for the sectors $i = 1, \dots, 5$. The supports (considering the five sectors) are given by $\text{supp}(X_{\text{CO}_2,i}) = [-11218, 63152]$, $\text{supp}(X_{\text{CH}_4,i}) = [15.8, 6443.9]$, $\text{supp}(X_{\text{N}_2\text{O},i}) = [54.5, 2423.4]$. Note that the support of $X_{\text{CO}_2,i}$ contains a negative range, due to the fact that in the forest and land use change sector, forests, soils and other vegetation remove CO_2 from the atmosphere (as mentioned earlier), acting as a carbon sink (instead of a carbon source). Therefore, the negative values indicate that more CO_2 is absorbed from the atmosphere than emitted. Higher values of the risk measures R_1 , R_2 , and R_3 indicate a higher risk for air pollution due to greenhouse gas emissions. The criteria weights in Step 3 of Phase 1 are defined as $w_1 = 2/3$, $w_2 = w_3 = 1/6$. The reason for this choice is to assign lower weights to value at risk and tail value at risk, as both are related to the tail of the distribution, and to give greater weight to the mean, more associated with the central part of the distribution.

Considering other frameworks and different safety-critical contexts (e.g., flood or public-health risk), for a general or overall risk analysis, if the aim is to focus on the mean while also gaining some insight or indication of the occurrence and influence of extreme events, this weight configuration for the risk measures may be appropriate. However, considering a more specific risk analysis, if the objective is to more strongly detect and to penalize very more situations in which extreme events occur, that have catastrophic consequences and must be avoided, then the combined weights of the two tail-risk measures can be higher than that of the mean (e.g. $w_1 = w_2 = w_3 = 1/3$, or, $w_1 = 2/10$, $w_2 = w_3 = 4/10$).

Remark 3 Besides the sensitivity analysis explained in Remark 2, a further robustness analysis will be carried out to study the effect of the risk criteria weight variation of w_1 , w_2 and w_3 on the risk ordering, considering the following experiments.

- Experiment 1: The Q_i scores are computed for criteria weight configurations satisfying (see Step 3 and Step 4 of Phase 1)

$$\sum_{j=1}^3 w_j = 1 \text{ and } w_1 > w_2 = w_3, \quad (9)$$

considering $w_1 = 0.4, 0.5, \dots, 1$, $w_2 = w_3 = \frac{1-w_1}{2}$. Then, the alternatives are ranked according to their Q_i score for each weight configuration.

- Experiment 2: The optimal Q_i score is computed for each alternative using the optimal weights, obtained by solving the following problem (see Step 3 and Step 4 of Phase 1):

$$\begin{aligned} \min_{w_1, w_2, w_3} \quad & Q_i(w_1, w_2, w_3) = 0.5 \sum_{j=1}^3 w_j r_{ij} + 0.5 \prod_{j=1}^3 (r_{ij})^{w_j} \\ \text{s.t.} \quad & w_1 > w_2 = w_3, \\ & \sum_{j=1}^3 w_j = 1, \\ & w_j \geq 0, \quad j = 1, 2, 3. \end{aligned} \quad (10)$$

Then, the alternatives are ranked based on their optimal Q_i scores.

4.1 Phase 1: WASPAS assessment for risk factors N_2O , CO_2 and CH_4

In the first phase, the WASPAS method will be applied to assess the risk of sectors considering separately each greenhouse gas as risk factor.

4.1.1 Risk factor N_2O

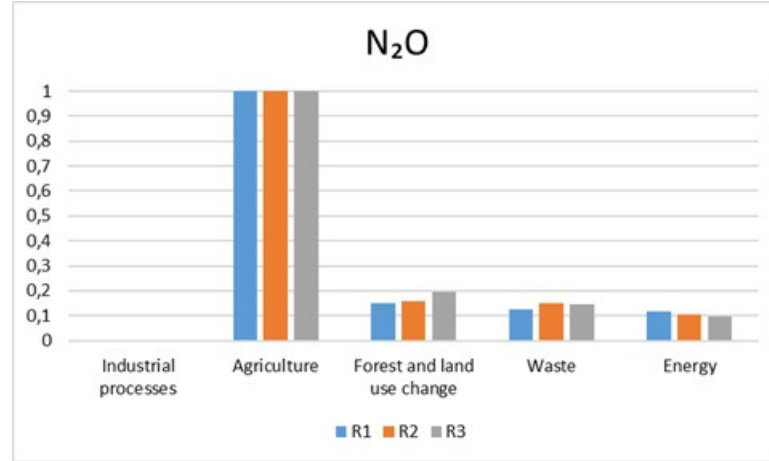
Considering the first risk factor $F_1 - \text{N}_2\text{O}$, applying the WASPAS multi-criteria decision making method leads to the following results. The risk decision matrix (defined in Step 1) is given by

$$M_{F_1} = \begin{matrix} & \begin{matrix} R_1 & R_2 & R_3 \end{matrix} \\ \begin{matrix} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \end{matrix} & \begin{pmatrix} 344.4 & 558.7 & 575.3 \\ 2166.4 & 2397.6 & 2410.5 \\ 619.1 & 851.3 & 930.4 \\ 570.3 & 835.9 & 844.5 \\ 562.1 & 748.9 & 750.3 \end{pmatrix} \end{matrix}.$$

The risk values in Table 2 are the entries r_{ij} , $i = 1, \dots, 5$, $j = 1, 2, 3$, of the normalized risk decision matrix R (see Step 2). The normalized risk values are represented graphically in Figure 5. One can confirm that the highest normalized risk values correspond all to the agricultural sector and the lowest to the industrial processes sector.

Table 2 Normalized risk values for N₂O.

A_i	sector	R_1	R_2	R_3
A_1	industrial processes	0.0000	0.0000	0.0000
A_2	agriculture	1.0000	1.0000	1.0000
A_3	forest and land use change	0.1508	0.1591	0.1935
A_4	waste	0.1240	0.1507	0.1467
A_5	energy	0.1195	0.1034	0.0954

**Fig. 5** Normalized risk values for N₂O.

Using the normalized risk values, the weighted sum WS_i , the weighted product WP_i (see Step 3), and the overall aggregated sum product score Q_i (defined in Step 4) are computed for all alternatives. The obtained results and the rank orders for the alternatives based on the sum product score (using the rule in Step 6) are listed in Table 3.

Table 3 Weighted sum, weighted product, Q_i score and ranks for N₂O.

A_i	sector	WS_i	WP_i	Q_i	rank
A_1	industrial processes	0.0000	0.0000	0.0000	1
A_2	agriculture	1.0000	1.0000	1.0000	5
A_3	forest and land use change	0.1593	0.1586	0.1589	4
A_4	waste	0.1322	0.1317	0.1320	3
A_5	energy	0.1128	0.1123	0.1126	2

Thus, the WASPAS method applied to the risk factor N_2O leads to the following risk order relation for the alternatives:

$$A_1 \prec A_5 \prec A_4 \prec A_3 \prec A_2,$$

so that agriculture is the riskiest sector for air pollution due to N_2O , followed by forest and land use change, whereas industrial processes is classified as least riskiest sector and energy as second less riskiest sector. The waste sector represents an intermediate risk level.

Next, a sensitivity analysis will be performed, computing the Q_i scores by varying the weights applied to the weighted sum and to the weighted product using (6). The results are presented in Table 4 and illustrated in Figure 6. One can state that, although small changes in the Q_i values occur for the alternatives A_3 , A_4 , A_5 (with the Q_i values for the alternatives with highest and with lowest risk remaining unchanged), the variation in λ does not affect the ranking of the alternatives. The ranking obtained for $\lambda = 0.5$ is not changed. Thus, the WASPAS method is robust under variations of weights assigned to the weighted sum and to the weighted product. This means that in this analysis, using the weighted product model or the weighted sum model would lead to the same risk decision.

Table 4 Values of Q_i for variations in λ for N_2O .

$A_i \backslash \lambda$	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
A_1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A_2	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
A_3	0.1586	0.1586	0.1587	0.1588	0.1589	0.1589	0.1590	0.1591	0.1591	0.1592	0.1593
A_4	0.1317	0.1318	0.1318	0.1319	0.1319	0.1320	0.1320	0.1321	0.1321	0.1322	0.1322
A_5	0.1123	0.1124	0.1124	0.1125	0.1125	0.1126	0.1126	0.1127	0.1127	0.1128	0.1128

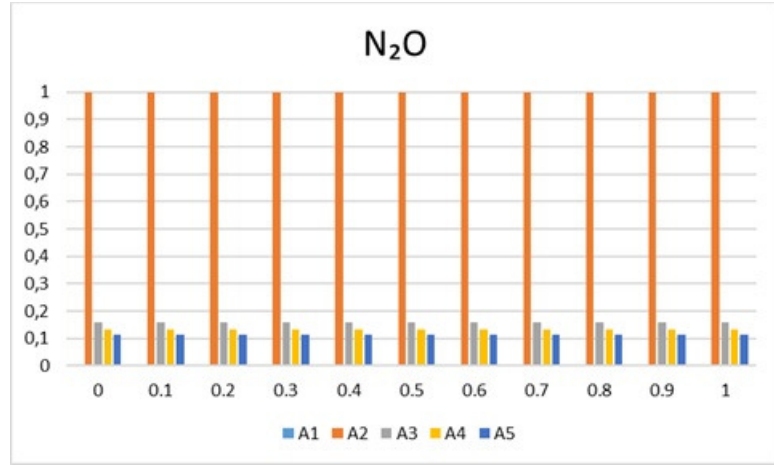


Fig. 6 Values of Q_i for variations in λ for N_2O .

Considering the robustness analysis explained in Remark 3, the first experiment yields the ranking results for $w_1 = 0.4, 0.5, \dots, 1$ (with $w_2 = w_3 = \frac{1-w_1}{2}$) listed in Table 5, where FR denotes the final ranking determined with the previously established weights (see Table 3) and AP represents the agreement percentage, determined from comparing the rank order of the alternative for each weight configuration with the final rank order in FR. The results show that the ranking remains unchanged for all considered weight configurations. In the second experiment, the optimal weights

Table 5 Ranking results for Experiment 1 for N_2O .

$A_i \setminus w_1$	0.4	0.5	0.6	0.7	0.8	0.9	1	FR	AP
A_1	1	1	1	1	1	1	1	1	100.00
A_2	5	5	5	5	5	5	5	5	100.00
A_3	4	4	4	4	4	4	4	4	100.00
A_4	3	3	3	3	3	3	3	3	100.00
A_5	2	2	2	2	2	2	2	2	100.00

and the corresponding optimal Q_i score for each alternative and resulting rank are presented in Table 6. Again, one can confirm that the previously obtained final ranking is recovered when using now the weights that optimize the Q_i score for a given alternative.

The reason for the stable ranking results in the previous analyses is that for N_2O , the risk values have the same ordering for the alternatives across the three risk measures (cf. Table 2), where A_2 attained the highest risk with all risk measures and A_1 the lowest risk. Although, for the risk factor N_2O , the final ranking and its stability was in fact expected, the methodology and analyses were carried out to illustrate their application and to confirm the expected results.

Table 6 Results for Experiment 2 for N₂O.

A_i	w_1	$w_2 = w_3$	Q_i	rank
A_1	0.5000	0.2500	0.0000	1
A_2	0.5000	0.2500	1.0000	5
A_3	1.0000	0.0000	0.1508	4
A_4	1.0000	0.0000	0.1240	3
A_5	0.3334	0.3333	0.1059	2

4.1.2 Risk factor CO₂

Calculating the risk values for the five sectors based on the CO₂ measurements, one gets the following risk decision matrix.

$$M_{F_2} = \begin{matrix} & R_1 & R_2 & R_3 \\ \begin{matrix} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \end{matrix} & \begin{pmatrix} 5433 & 6949 & 7002 \\ 48 & 65 & 66 \\ -4930 & 5705 & 12413 \\ 15 & 37 & 37 \\ 49244 & 62768 & 62960 \end{pmatrix} \end{matrix}.$$

Note that the mean value (corresponding to R_1) for the sector forest and land use change is negative, since, as explained before, forests remove CO₂ from the atmosphere.

Normalizing the risk values using the min-max normalization leads to the results in Table 7. The energy sector displays the highest normalized risk values.

Table 7 Normalized risk values for CO₂.

A_i	sector	R_1	R_2	R_3
A_1	industrial processes	0.1913	0.1102	0.1107
A_2	agriculture	0.0919	0.0005	0.0005
A_3	forest and land use change	0.0000	0.0904	0.1967
A_4	waste	0.0913	0.0000	0.0000
A_5	energy	1.0000	1.0000	1.0000

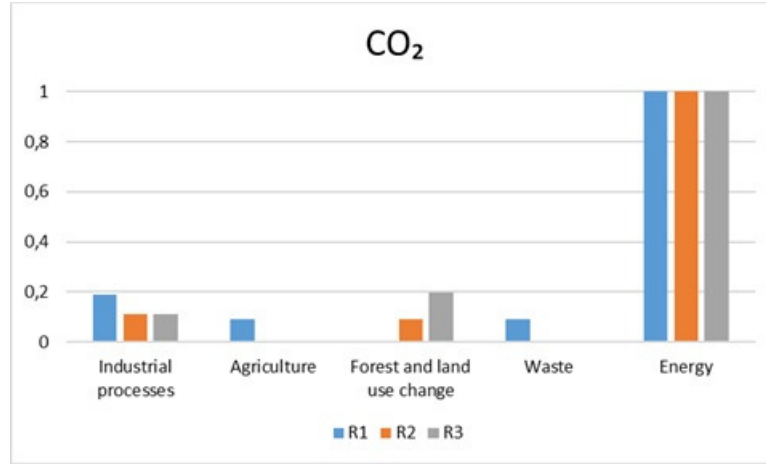


Fig. 7 Normalized risk values for CO₂.

Notably is that the sector forest and land use change records the second highest tail value at risk, despite the negative mean (and therefore the lowest risk value achieved with R_1). The high tail value at risk can be explained by the fact that the severe forest fires in 2017 in Portugal had a significant impact on CO₂ emissions (in the forest and land use change sector). In 2017, the annual average of CO₂ is 19120.2 (kt of CO₂ equivalent), an extreme value that leads to the very high expected value exceeding the value at risk. Also the value at risk of this sector is considerable high (the third highest value at risk).

Table 8 contains the weighted sum WS_i , weighted product WP_i , the overall aggregated sum product score Q_i and the rank orders for the alternatives obtained from the application of the WASPAS method. According to the WASPAS ranking, the risk

Table 8 Weighted sum, weighted product, Q_i score and ranks for CO₂.

A_i	sector	WS_i	WP_i	Q_i	rank
A_1	industrial processes	0.1643	0.1593	0.1618	4
A_2	agriculture	0.0614	0.0157	0.0386	3
A_3	forest and land use change	0.0478	0.0000	0.0239	1
A_4	waste	0.0608	0.0000	0.0304	2
A_5	energy	1.0000	1.0000	1.0000	5

order relation for the sectors taking into account the emissions of CO₂ is:

$$A_3 \prec A_4 \prec A_2 \prec A_1 \prec A_5.$$

The energy sector is now classified as the riskiest sector for the emission of this greenhouse gas and forest and land use change as the least risky sector.

Conducting the sensitivity analysis based on the λ weight variation in (6), the results in Table 9 show that the overall aggregated scores Q_i exhibit small changes for all alternatives except for the riskiest alternative A_5 ($Q_5 = 1$). However, the changes do not alter the previous ranking established for $\lambda = 0.5$ (see Figures 8, 9), only for $\lambda = 0$, where the WASPAS method reduces to the weighted product model, a tie occurs between the two lowest risk alternatives A_3 and A_4 , which is then solved for non-zero λ values. One can also observe that increasing λ , that is adding and increasing the contribution of the weighted sum, raises the Q_i scores for A_i , $i = 1, 2, 3, 4$. One can conclude that for CO_2 the risk decision is invariant under changes in λ .

Table 9 Values of Q_i for variations in λ for CO_2 .

$A_i \backslash \lambda$	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
A_1	0.1593	0.1598	0.1603	0.1608	0.1613	0.1618	0.1623	0.1628	0.1633	0.1638	0.1643
A_2	0.0157	0.0203	0.0248	0.0294	0.0340	0.0386	0.0431	0.0477	0.0523	0.0568	0.0614
A_3	0.0000	0.0048	0.0096	0.0144	0.0191	0.0239	0.0287	0.0335	0.0383	0.0431	0.0478
A_4	0.0000	0.0061	0.0122	0.0183	0.0243	0.0304	0.0365	0.0426	0.0487	0.0548	0.0608
A_5	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

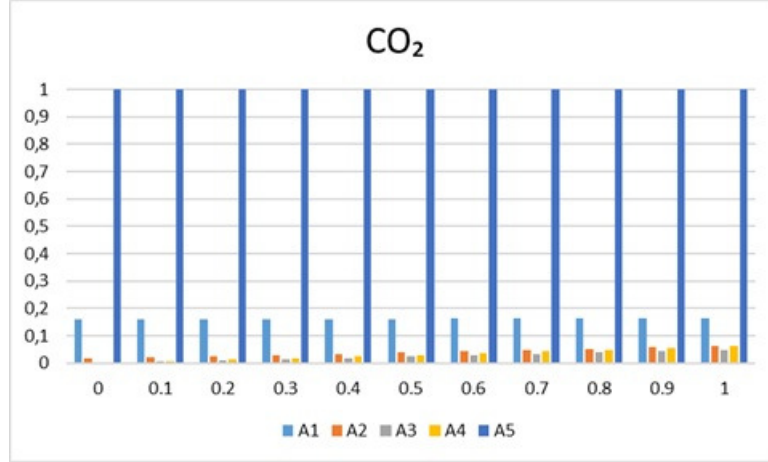


Fig. 8 Values of Q_i for variations in λ for CO_2 .

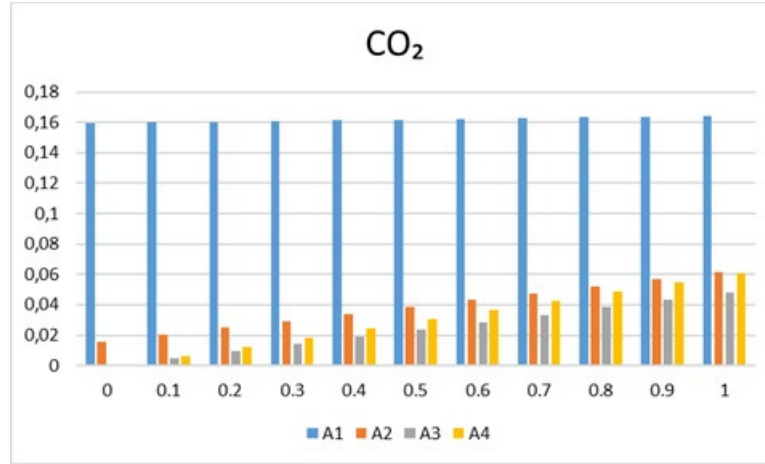


Fig. 9 Values of Q_i for variations in λ for CO₂ (excluding the riskiest alternative for a better graphical visualization).

Applying the robustness analysis described in Remark 3, the first experiment leads to the ranking results for $w_1 = 0.4, 0.5, \dots, 1$ (with $w_2 = w_3 = \frac{1-w_1}{2}$) in Table 10. One can observe that the rank orders of the alternatives with highest risk, A_5 and A_1 , remain unchanged for the considered weight configurations. The agreement percentages indicate that the alternatives A_3 and A_4 are the most unstable alternatives, followed by A_2 . Increasing w_1 , that is, assigning a higher weight to the mean risk measure while reducing the weights of the tail risk measures, decreases the risk of A_3 , and increases the risk of A_2 and A_4 . Considering the second experiment, calculating the

Table 10 Ranking results for Experiment 1 for $w_1 = 0.4, 0.5, \dots, 1$ for CO₂.

$A_i \backslash w_1$	0.4	0.5	0.6	0.7	0.8	0.9	1	FR	AP
A_1	4	4	4	4	4	4	4	4	100.00
A_2	2	2	3	3	3	3	3	3	71.43
A_3	3	3	2	1	1	1	1	1	57.14
A_4	1	1	1	2	2	2	2	2	57.14
A_5	5	5	5	5	5	5	5	5	100.00

optimal weights and the corresponding optimal Q_i score for each alternative and the resulting rank leads to the results in Table 11. One can see that ranking the alternatives with respect to their optimal Q_i score produces the same ranking obtained with the previously established weights in Table 8.

For the risk factor CO₂, although the final ranking is preserved for the optimal weights in Experiment 2 and for weight configurations with $w_1 \geq 0.7$ in Experiment 1, the sensitivity of alternatives A_2 , A_3 , and A_4 , in particular of the forest and land

Table 11 Results for Experiment 2 for CO₂.

A_i	w_1	$w_2 = w_3$	Q_i	rank
A_1	0.3334	0.3333	0.1350	4
A_2	0.3334	0.3333	0.0169	3
A_3	1.0000	0.0000	0.0000	1
A_4	0.3334	0.3333	0.0152	2
A_5	0.5000	0.2500	1.0000	5

use change sector A_3 , for extreme values detected with the tail risk measures becomes evident (cf. Table 10).

4.1.3 Risk factor CH₄

Considering the CH₄ measurements, the risk decision matrix for the risk factor F_3 –CH₄ reads

$$M_{F_3} = \begin{matrix} & R_1 & R_2 & R_3 \\ \begin{matrix} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \end{matrix} & \begin{pmatrix} 25.9 & 31.5 & 31.9 \\ 4932.5 & 5213.9 & 5226.1 \\ 277.1 & 992.8 & 1167.5 \\ 5297.9 & 6440.6 & 6442.2 \\ 525.2 & 769.9 & 782.1 \end{pmatrix} \end{matrix}.$$

The values of the normalized risk decision matrix are presented in Table 12 and illustrated graphically in Figure 10.

Table 12 Normalized risk values for CH₄.

A_i	sector	R_1	R_2	R_3
A_1	industrial processes	0.0000	0.0000	0.0000
A_2	agriculture	0.9307	0.8086	0.8103
A_3	forest and land use change	0.0476	0.1500	0.1772
A_4	waste	1.0000	1.0000	1.0000
A_5	energy	0.0947	0.1152	0.1170

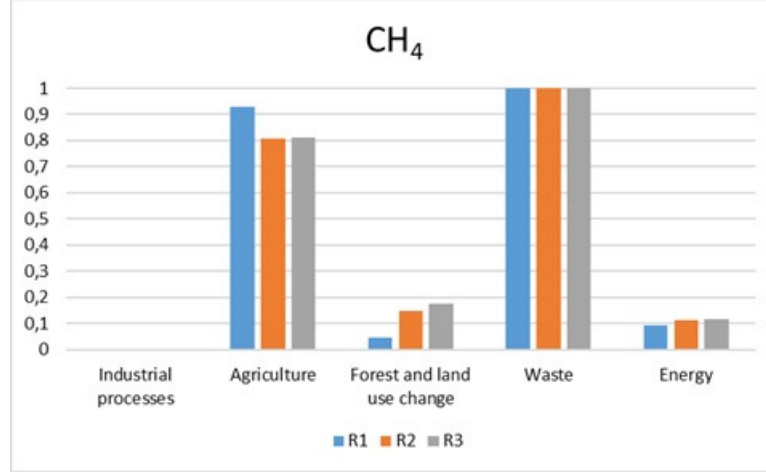


Fig. 10 Normalized risk values for CH₄.

One can observe that the sector waste attains the maximum values with respect to all three risk measures and industrial processes the minimum values.

Proceeding with the WASPAS method, one gets the results for the weighted sum WS_i , weighted product WP_i , overall aggregated sum product score Q_i and rank orders for the sectors in Table 13. As expected, in this case, the sector waste is classified as the

Table 13 Weighted sum, weighted product, Q_i score and ranks for CH₄.

A_i	sector	WS_i	WP_i	Q_i	rank
A_1	industrial processes	0.0000	0.0000	0.0000	1
A_2	agriculture	0.8903	0.8884	0.8893	4
A_3	forest and land use change	0.0863	0.0718	0.0790	2
A_4	waste	1.0000	1.0000	1.0000	5
A_5	energy	0.1018	0.1014	0.1016	3

riskiest sector for the emission of CH₄. On the contrary, the sector industrial processes exhibits the lowest risk. The final WASPAS risk ranking of the sectors considering the emission risk of the greenhouse gas CH₄ is:

$$A_1 \prec A_3 \prec A_5 \prec A_2 \prec A_4.$$

Table 14 contains the values of the overall aggregated Q_i scores obtained for the sensitivity analysis with respect to λ using (6). One can see that the Q_i scores for the lowest risk and highest risk alternatives, A_1 and A_4 respectively, remain the same ($Q_1 = 0$ and $Q_4 = 1$) and that the score values of the other alternatives increase slightly with λ . However, the effect of these changes have no observable impact on

the ranking and does not change the final ranking pattern (see Figure 11). Therefore, the WASPAS method also demonstrates stability and consistency in risk assessment for the CH₄ pollutant, concerning changes in the weights assigned to the weighted product and weighted sum components.

Table 14 Values of Q_i for variations in λ for CH₄.

$A_i \backslash \lambda$	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
A_1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A_2	0.8884	0.8886	0.8888	0.8889	0.8891	0.8893	0.8895	0.8897	0.8899	0.8901	0.8903
A_3	0.0718	0.0732	0.0747	0.0761	0.0776	0.0790	0.0805	0.0819	0.0834	0.0848	0.0863
A_4	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
A_5	0.1014	0.1014	0.1015	0.1015	0.1016	0.1016	0.1017	0.1017	0.1018	0.1018	0.1018

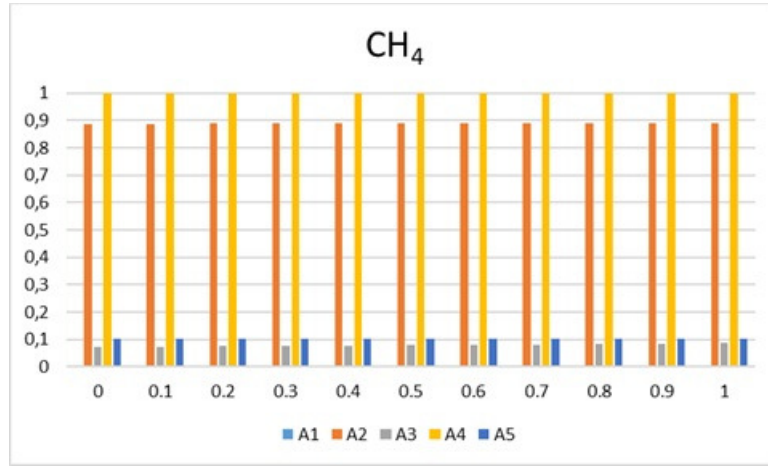


Fig. 11 Values of Q_i for variations in λ for CH₄.

Considering the robustness analysis described in Remark 3, for the first experiment one obtains the ranking results for $w_1 = 0.4, 0.5, \dots, 1$ (with $w_2 = w_3 = \frac{1-w_1}{2}$) presented in Table 15. The results show that only one rank reversal occurs between A_3 and A_5 when changing w_1 from 0.4 to 0.5, otherwise, the ranking remains unchanged from 0.5 to 1 and coincides with the final ranking established previously in Table 13.

Considering the second experiment, calculating the optimal weights and the corresponding optimal Q_i score for each alternative and the resulting rank, leads to the results in Table 16. One can see that ranking the alternatives with respect to their optimal Q_i score produces the same ranking as that obtained using the previously established weights in Table 13.

Table 15 Ranking results for Experiment 1 for $w_1 = 0.4, 0.5, \dots, 1$ for CH₄.

$A_i \backslash w_1$	0.4	0.5	0.6	0.7	0.8	0.9	1	FR	AP
A_1	1	1	1	1	1	1	1	1	100.00
A_2	4	4	4	4	4	4	4	4	100.00
A_3	3	2	2	2	2	2	2	2	85.71
A_4	5	5	5	5	5	5	5	5	100.00
A_5	2	3	3	3	3	3	3	3	85.71

Table 16 Results for Experiment 2 for CH₄.

A_i	w_1	$w_2 = w_3$	Q_i	rank
A_1	0.5000	0.2500	0.0000	1
A_2	0.3334	0.3333	0.8489	4
A_3	1.0000	0.0000	0.0476	2
A_4	0.5000	0.2500	1.0000	5
A_5	1.0000	0.0000	0.0947	3

For the risk factor CH₄, almost all weights configurations generate the same final ranking, except that for $w_1 = 0.4$ in Experiment 1, indicating that the alternatives A_3 and A_5 have associated extreme emission values (that are not detected by the mean), since in that configuration a higher weight is assigned to both tail risk measures than to the mean.

4.2 Phase 2: WBR aggregation

The next phase consists now in aggregating the three WASPAS ranking outputs obtained for the three greenhouse gases using the weighted Borda ranking method. The risk ranking matrix Z (see Step 1 of Phase 2) contains the rankings for each alternative according to each risk factor ($F_1 - \text{N}_2\text{O}$, $F_2 - \text{CO}_2$, $F_3 - \text{CH}_4$):

$$Z = \begin{matrix} & F_1 & F_2 & F_3 \\ \begin{matrix} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \end{matrix} & \begin{pmatrix} 1 & 4 & 1 \\ 5 & 3 & 4 \\ 4 & 1 & 2 \\ 3 & 2 & 5 \\ 2 & 5 & 3 \end{pmatrix} \end{matrix}.$$

In order to establish the weights for the application of the weighted Borda score in Step 2, the contribution of the emission of each greenhouse gas is determined with respect to the total emission in the given study period from 1990 to 2022 (considering only the emissions of the three greenhouse gases). The results revealed that out of a total of $TE = 65132.1270$ kt of greenhouse gas emissions (in CO₂ equivalent), $TE_{F_1} = 4262.2576$ kt were attributed to N₂O, $TE_{F_2} = 49811.2727$ kt to CO₂, and $TE_{F_3} = 11058.5970$ kt to CH₄. Therefore, the weights, representing the relative contribution

of each gas to the total emission, will be defined by

$$w_k = \frac{TE_{F_k}}{TE}, \quad k = 1, 2, 3,$$

yielding

$$w_1 = 0.07, \quad w_2 = 0.76 \quad w_3 = 0.17,$$

(rounded to two decimal places). Calculating the weighted Borda scores using formula (7) and determining the weighted Borda ranking (see Step 3 in Phase 2) leads to the results displayed in Table 17.

Table 17 Risk rank orders of the alternatives for the risk factors F_1 – N_2O , F_2 – CO_2 , F_3 – CH_4 , weighted Borda scores (WBS) and weighted Borda ranking (WBR).

A_i	sector	N_2O	CO_2	CH_4	WBS	WBR
A_1	industrial processes	1	4	1	3.28	3
A_2	agriculture	5	3	4	3.31	4
A_3	forest and land use change	4	1	2	1.38	1
A_4	waste	3	2	5	2.58	2
A_5	energy	2	5	3	4.45	5
weights		0.07	0.76	0.17		

The results show that the risk factor CO_2 , due to the higher associated weight, has a high influence on the final WBR ranking, as expected. However the final WBR ranking is different from the CO_2 ranking, indicating that the other two risk factors also have an impact on the final ranking. In particular, the risk positions of A_1 and A_2 (in the final WBR ranking 3 and 4, respectively) are different from those of the CO_2 ranking (4 and 3 respectively). One can observe that the weighted Borda scores of A_1 and A_2 are very similar and, thus, the corresponding risk positions in the final WBR ranking are more sensitive than the risk positions of the other alternatives.

One concludes that the final risk classification of the sectors, considering the emissions of the greenhouse gases N_2O , CO_2 , CH_4 is

$$A_3 \prec A_4 \prec A_1 \prec A_2 \prec A_5.$$

Thus, energy is the riskiest sector and agriculture is the second riskiest sector for the emissions of these air pollutants. The sector industrial processes represents an intermediate risk level. The lowest risk for air pollution due to the greenhouse gases is attributed to the forest and land use change sector. The sector waste is classified as having the second lowest risk.

5 Conclusion

In this work, a combined multi-criteria decision making and rank aggregation approach, WASPAS-WBR, has been developed for risk assessment problems, integrating the weighted aggregated sum product assessment (WASPAS) method and the weighted Borda ranking (WBR). The method permits classifying alternatives in terms of risk, by taking into account, on the one hand, the different risk characteristics of data through the risk measures and, on the other hand, the contribution of different risk factors to the assessment of the total risk. The criteria in the WASPAS method were defined by the risk measures: mean, value at risk and tail value at risk. The advantage of using this combined risk measurement approach is that, in addition to the mean, which provides an overall evaluation of the observed feature, the value at risk estimates an adverse outcome at a specific probability level, while the tail value at risk focuses on the average outcome beyond the threshold given by the value at risk. In particular, the tail value at risk is sensible for extreme events and penalizes alternatives with extreme values in the risk classification, whereas the simple mean neglects this aspect.

Since in several problems the contribution of different risk factors has to be analysed and considered for the risk assessment of the alternatives, in the here proposed approach the WASPAS method is applied separately for each risk factor, resulting in one independent ranking of alternatives for each risk factor. Then, the rankings are aggregated using the weighted Borda ranking. Thereby, different weights permit differentiate the importance of each risk factor to the total risk contribution.

The WASPAS-WBR approach has been applied to the risk assessment of sectors for greenhouse gas emission in Portugal. Annual average data of the air pollutants CO₂, CH₄ and N₂O (emissions in kt of CO₂ equivalent), in the time interval from 1990 to 2022, extracted from the Portuguese Institute of Statistics (INE), have been considered.

The risk analysis of greenhouse gas emission by sectors due to the risk factors CO₂, CH₄, N₂O has led to the following final risk ranking (from the lowest to the highest risk):

$$\text{forest and land use change} \prec \text{waste} \prec \text{industrial processes} \prec \\ \text{agriculture} \prec \text{energy}.$$

Energy has been identified as the highest risk sector for air pollution due to greenhouse gas emissions and forest and land use change has been classified as the lowest risk sector. As for the individual rankings by risk factors, the results have revealed that energy is the riskiest sector for the emission of CO₂, agriculture is the riskiest sector for N₂O, and waste is the riskiest sector for the emission of CH₄. In the considered study period, CO₂ accounted for 76% of total (CO₂ and CH₄ and N₂O) greenhouse gas emissions, CH₄ was responsible for 17% of the total emissions, and N₂O accounted for 7% of the total greenhouse gas emissions. A sensitivity analysis has been conducted to examine how variations in the weights assigned to the WASPAS components weighted sum and weighted product affect the risk classification of the alternatives concerning each air pollutant. The results permitted concluding that the WASPAS method is

robust with respect to these changes and thus, in this study, the risk decisions are invariant under convex combinations of the weighted sum and weighted product model. Also, a robustness analysis with different risk criteria weight configurations has been carried out, where slight changes in risk order positions occurred due to the influence of existing extreme values detected with the tail risk measures, when considering CO₂ and CH₄.

The proposed approach has been illustrated through its application to an air pollution risk assessment problem, however it can be adapted and applied to many risk assessment problems in other different contexts (e.g. in the environmental context or financial context), where the aim is to assess the risk of alternatives according to different risk factors.

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Declarations

The author has no competing interests to declare.