Supplementary Material

Contents

1 Description of the considered multi-criteria decision-making (MCDM) methods

The computational details of the selected MCDM methods are described in the following subsections.

1.1 Simple Additive Weighting

Simple Additive Weighting (SAW), or Weighted Sum Model (WSM) (Fishburn, 1967), is probably the most common MCDM method. It is one of the simplest techniques, very popular also among practitioners (Zanakis et al., 1998).

The principle behind this technique is the additive utility assumption since alternatives are ranked based of their weighted sum performance. The weights w_j are directly assigned to criteria by decision-maker(s). Equation (1) is used to calculate the final performance value for the i-th alternative, $P(A_i)$:

$$P(A_i) = \sum_{j=1}^{n} w_j \cdot r_{ij} \qquad (1)$$

where n is the number of criteria, w_j is the weight of each criterion and r_{ij} is the normalized score of alternative A_i with respect to criterion j.

Indeed, the method is formulated for problems in which all the considered criteria are numerical and expressed in the same unit. Moreover, all criteria should be benefit-type (maximization problem) or cost-type (minimization problem). Therefore, if the variables are not comparable, the decision matrix needs to be normalized, in order to add up non-dimensional values (Carriço et al., 2014).

The normalized value r_{ij} can be calculated as follows, for benefit criteria:

$$r_{ij} = \frac{x_{ij} - x_{min,j}}{x_{max,j} - x_{min,j}} \qquad (2)$$

and for cost criteria:

$$r_{ij} = \frac{x_{max,j} - x_{ij}}{x_{max,j} - x_{min,j}} \qquad (3)$$

where x_{ij} is the score of alternative A_i with respect to criterion C_j, while $x_{min,j}$ and $x_{max,j}$ are the minimum value and the maximum value, respectively, for each criterion j (Geldermann and Schöbel, 2011).

The best alternative is the one with the highest $P(A_i)$ value, for a maximization decision problem (and with the lowest $P(A_i)$ value for a minimization problem) (Caterino et al., 2009).

1.2 Weighted Product Method

The Weighted Product Method (WPM) is very similar to the SAW, but it uses multiplication, instead of addition, to connect the decision matrix values (Bridgman, 1922).

Each alternative is compared with the others by multiplying different ratios, one for each criterion. Each ratio is raised to the power of the corresponding criterion weight (defined by decision-makers). Therefore, to compare the two alternatives A_k and A_l (where $1 \leq k, l \leq m$), Equation (4) is used:

$$R\left(\frac{A_k}{A_l}\right) = \prod_{j=1}^{n} \left(\frac{x_{kj}}{x_{lj}}\right)^{w_j} \qquad (4)$$

Alternative A_k is better than A_l if the value $R\left(\frac{A_k}{A_l}\right)$ is higher than or equal to 1 when the criteria are benefit-type (lower than 1 for cost criteria). The optimal alternative is the one that is better than (or at least equal to) all the other alternatives (Triantaphyllou and Mann, 1989).

The structure of the method eliminates all the different units of measure, performing a "dimensionless analysis". Therefore, the WPM method can also be used in multi-dimensional decision problems. However, it requires that all the criteria are of the same type, i.e., benefit or cost (Caterino et al., 2009).

An alternative approach of this method consists in calculating, for each alternative, the following performance value, $P(A_i)$:

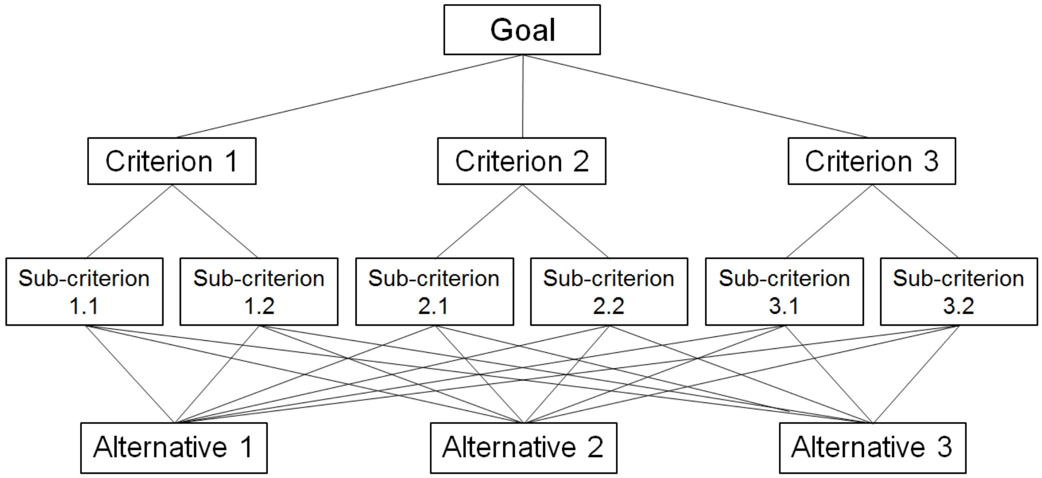
$$P(A_i) = \prod_{j=1}^{n} \left(x_{ij}\right)^{w_j} \qquad (5)$$

The alternatives are ranked based on their total performance value: the optimal alternative is the one with the highest $P(A_i)$ (Athawale and Chakraborty, 2012).

1.3 Analytic Hierarchy Process

The Analytic Hierarchy Process (AHP) was developed by Thomas L. Saaty in the 1970s (Saaty, 1980) and it has been widely used to solve MCDM problems in different fields. The method is based on the multi-attribute utility theory and allows the breakdown of complex problems into a hierarchical structure, thus facilitating the assignment of judgements by decision-makers (Altunok et al., 2010).

The application of the AHP method can be divided into four main steps (Kiciński and Solecka, 2018). In the first step, a hierarchical structure of the problem is defined, with the goal at the top level, criteria and (if applicable) sub-criteria at the intermediate levels, and alternatives at the bottom of the hierarchy (Athawale and Chakraborty, 2012). Supplementary Figure 1 shows an example of a decision problem hierarchy in the AHP method.



Supplementary Figure 1. Example of the hierarchical structure of a decision-making problem.

The next step involves the decision-maker(s) in the determination of subjective preferences, by means of pairwise comparisons. Therefore, different pairwise comparison matrices are developed for each level of the hierarchical structure. On each hierarchy level, elements are compared in pairs among themselves with respect to each of the elements in the next higher level. For these pairwise comparisons, the fundamental scale of Saaty (Saaty, 1980) is used to measure how many times an element is more important over another one (Supplementary Table 1). 1 corresponds to equal importance between two elements, while 9 represents a strong preference for the first element compared to the second one (Sarraf and McGuire, 2020).

Supplementary Table 1. The fundamental scale of Saaty for comparisons in AHP.

Intensity of importance	Definition
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	Intermediate values

Therefore, each pairwise comparison matrix C is a positive reciprocal square matrix, where $a_{ij} = 1$ when $i = j$ (i.e., all the main diagonal values are equal to 1 because they correspond to the self-comparison of the elements) and $a_{ji} = a_{ij}$ (where a_{ij} is the relative importance of i-th element over j-th element) (Athawale and Chakraborty, 2012). For example, if n elements are compared, the following matrix is calculated:

$$C = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ 1/a_{12} & 1 & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ 1/a_{1n} & 1/a_{2n} & \dots & 1 \end{bmatrix} \qquad (6)$$

The number of judgements for such a matrix of order n is $n \cdot (n-1)/2$ (Sarraf and McGuire, 2020).

Therefore, for each pairwise matrix, a vector of priorities is calculated by finding the eigenvector with the largest eigenvalue (λ_{max}) (Saaty 1980). This vector represents the relative importance of the different elements being compared.

The third step concerns the study of the consistency of the pairwise comparison, at each level of the hierarchy. In other words, it aims at checking the consistency of the judgements provided by the decision-maker(s) in the previous phase. Two indexes are calculated, i.e., the consistency index (CI):

$$CI = \frac{\lambda_{max} - n}{n - 1} \qquad (7)$$

and the consistency ratio (CR):

$$CR = \frac{CI}{RI} \qquad (8)$$

where RI is the consistency index of a random matrix of the same size (with randomly chosen judgments).

The smaller the values of these indexes, the more consistent the judgements of the decision-maker are. A CR value of 0.10 or less is considered acceptable; otherwise, it is necessary to revise the preferential information introduced in the second phase (Athawale and Chakraborty, 2012).

The last step concerns the calculation of the overall performance value for each alternative. Composite weights are determined by aggregating the weights of the elements throughout the hierarchy. An additive utility function is used, multiplying the weights along the path from the top of the hierarchy down to each alternative. The result is a normalized eigenvector with the overall weights of the alternatives (Saaty, 1980). Based on these values, the final ranking of the alternatives is obtained: the preferred alternative, in a maximization problem, is the one with the highest performance value (Kiciński and Solecka, 2018).

It has to be highlighted that AHP is frequently used in combination with other MCDM methods (e.g., Saracoglu, 2015; Ameri et al., 2018): it provides a more organized structure to the problem and assists decision-makers in determining the weights for criteria and sub-criteria, which are subsequently used in the other method.

Several software packages can be used to develop the AHP model. *ExpertChoice*, *SuperDecisions*, *MakeItRational*, etc. are among the most common (Kumar and Katoch, 2015).

1.4 Technique for Order Preference by Similarity to Ideal Solution

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is a distance-based method, first introduced by Hwang and Yoon (1981). The basic idea is that the preferred alternative should have the shortest Euclidean distance from the ideal solution (A^*) and the farthest distance from the negative-ideal solution (A^-).

The TOPSIS procedure consists of the following seven steps (Opricović and Tzeng, 2004).

Step 1: Normalize the decision matrix. The normalized values r_{ij} are calculated using Equation (9):

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{n}(x_{ij})^2}} \qquad (9)$$

Step 2: Calculate the weighted normalized values as $v_{ij} = w_j \cdot r_{ij}$, where w_j is the weight of the j-th criterion, assigned by decision-makers.

Step 3: Calculate the ideal solution (A^*) and the negative-ideal solution (A^-):

$$A^* = \{v_1^*, \dots, v_n^*\} = \left\{\left(\max_j v_{ij} \mid j \in I^*\right), \left(\min_j v_{ij} \mid j \in \mathrm{I}^-\right)\right\} \qquad (10)$$

$$A^- = \{v_1^-, \dots, v_n^-\} = \left\{\left(\min_j v_{ij} \mid j \in I^*\right), \left(\max_j v_{ij} \mid j \in \mathrm{I}^-\right)\right\} \qquad (11)$$

where I^* is a set of benefit criteria and I^- is a set of cost criteria.

Step 4: Calculate the distance of each alternative from the ideal solution (D_i^*) and from the negative-ideal solution (D_i^-), using the n-dimensional Euclidean distance:

$$D_i^* = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^*\right)^2} \qquad (12)$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2} \qquad (13)$$

Step 5: Calculate the relative closeness of each alternative to the ideal solution (RC_i):

$$RC_i = \frac{D_i^-}{(D_i^* + D_i^-)} \qquad (14)$$

Step 6: Rank the alternatives according to the value of RC_i in descending order. The best alternative is the one with the highest RC_i (Wang et al., 2014).

1.5 VIKOR method

VIKOR (*VIšekriterijumsko KOmpromisno Rangiranje* – multicriteria optimization and compromise ranking) (Opricović, 1998) was developed to solve complex MCDM problems, characterized by conflicting and non-commensurable evaluation criteria. The method assumes that a compromise, based on mutual concessions made between the alternatives, can be accepted for solving the conflict. Therefore, it introduces the multi-criteria ranking index based on the closeness to the ideal solution. The compromise solution (one or more alternatives) is always feasible and it is the closest to the ideal solution (Vučijak et al., 2013).

The L_p-metric, used in compromise programming method, is introduced to represent the relative distance of alternatives from the ideal solution. The following form of L_p-metric is considered:

$$L_{p,i} = \left\{ \sum_{j=1}^{n} \left[w_j \left((x_{ij})_{max} - x_{ij} \right) / \left((x_{ij})_{max} - (x_{ij})_{min} \right) \right]^p \right\}^{1/p} , 1 \leq p \leq \infty \qquad (15)$$

The compromise ranking algorithm VIKOR has the following steps (Opricović and Tzeng, 2004).

Step 1: Determine the best (f_j^*) and the worst (f_j^-) values of each criterion. If the j-th criterion represents a benefit, they can be calculated as follows:

$$f_j^* = \max_i x_{ij} \ , \qquad f_j^- = \min_i x_{ij} \qquad (16)$$

Step 2: Calculate the values S_i and R_i, using the following relations:

$$S_i = \sum_{j=1}^{n} \frac{w_j \cdot \left(f_j^* - x_{ij} \right)}{f_j^* - f_j^-} \qquad (17)$$

$$R_i = \max_j \left[w_j \cdot (f_j^* - x_{ij}) / (f_j^* - f_j^-) \right] \qquad (18)$$

where w_j are the weights of criteria, assigned by decision-makers.

Step 3: Calculate the values Q_i using Equation (19):

$$Q_i = \frac{\upsilon (S_i - S^*)}{S^- - S^*} + \frac{(1 - \upsilon)(R_i - R^*)}{R^- - R^*} \qquad (19)$$

where:

$$S^* = \min_i S_i \ , \qquad S^- = \max_i S_i \qquad (20)$$

$$R^* = \min_i R_i \ , \qquad R^- = \max_i R_i \qquad (21)$$

Coefficient υ is a weight for the strategy of “the majority of criteria”, while $(1 - \upsilon)$ is the weight of “the individual regret”. The coefficient is defined by the decision-maker in the interval [0,1]. If $\upsilon >$ 0.5, more importance is given to satisfying most of the criteria, while using a υ value lower than 0.5, more weight is given to the second term of Q, i.e., to minimizing the individual differences of the alternatives, for each single criterion, from the ideal solution. These strategies can be compromised considering υ = 0.5 (Opricović and Tzeng, 2008).

Step 4: Rank the alternatives, based on the values of S, R and Q, in decreasing order. Therefore, the results are three ranking lists.

Step 5: Propose as a compromise solution the alternative $A^{(1)}$, which is the best ranked by the measure Q (i.e., the alternative with the minimum value of Q), if the following two conditions are satisfied:

1) "Acceptable advantage":

$$Q\left(A^{(2)}\right) - Q\left(A^{(1)}\right) \geq DQ \qquad (22)$$

where $A^{(2)}$ is the alternative with the second position in the ranking by Q and $DQ = 1/(m-1)$;

2) "Acceptable stability in decision-making": alternative $A^{(1)}$ must also be the best ranked by S or/and R.

If one of the conditions is not satisfied, it is not possible to directly select the preferred solution, but a set of compromise solutions can be defined, which consists of:

- Alternatives $A^{(1)}$ and $A^{(2)}$, if only the second condition is not satisfied, or
- Alternatives $A^{(1)}, A^{(2)}, \ldots, A^{(k)}$, if the first condition is not satisfied, where $A^{(k)}$ is the last alternative, in the ranking by Q, for which the relation $Q\left(A^{(k)}\right) - Q\left(A^{(1)}\right) < DQ$ is still valid.

Therefore, the results of the VIKOR method are three rankings (by Q, S and R), and the proposed compromise solution (one or a set) with the "advantage rate" (Opricović and Tzeng, 2004).

1.6 ELECTRE III method

ELECTRE (ELimination Et Choix Traduisant la RÉalité – elimination and choice expressing the reality) methods are a family of MCDM techniques developed in France in the 1960s by Bernard Roy (Roy, 1968). After the first version (ELECTRE I), new methods of this family were developed, aimed at solving different types of decision problems, like choice, ranking or sorting.

ELECTRE III (Roy, 1978) is used to define a ranking of the alternatives. The novelty of this method is the introduction of pseudo criteria, instead of true criteria, to take into account the imperfect nature of the evaluation of alternatives. Therefore, three thresholds have to be introduced by the decision-maker(s) for each criterion j: an indifference threshold q_j, a preference threshold p_j, and a veto threshold v_j (Figueira et al., 2005). The following rule has to be considered: $q_j < p_j < v_j$.

The preference model is based on an outranking binary relation between alternatives, denoted as *S*, which means "at least as good as". Considering two alternatives A_1 and A_2, the following outranking relations may occur (Figueira et al., 2005):

- $A_1\ S\ A_2$ and not $A_2\ S\ A_1$: $A_1\ P\ A_2$, i.e., A_1 is strictly preferred to A_2

- $A_2\ S\ A_1$ and not $A_1\ S\ A_2$: $A_1\ P^-\ A_2$, i.e., A_2 is strictly preferred to A_1 or A_1 is inversely preferred to A_2
- $A_1\ S\ A_2$ and $A_2\ S\ A_1$: $A_1\ I\ A_2$, i.e., A_1 is indifferent to A_2
- Not $A_1\ S\ A_2$ and not $A_2\ S\ A_1$: $A_1\ R\ A_2$, i.e., A_1 is incomparable to A_2

The outranking relation $A_1\ S\ A_2$ is true if a sufficient majority of criteria is in favor of it (concordance) and none of the criteria opposes too strongly (non-discordance or non-veto). Therefore, concordance and discordance are evaluated by using the following indexes (Figueira et al., 2005):

i) The concordance index $C_j(A_i, A_k)$ of the alternatives A_i and A_k, for each criterion j, is calculated through Equation (23):

$$C_j(A_i, A_k) = \begin{cases} 0 & if\ g_j(A_i) \le g_j(A_k) - p_j \\ 1 & if\ g_j(A_i) > g_j(A_k) - q_j \\ \dfrac{p_j - [g_j(A_k) - g_j(A_i)]}{p_j - q_j} & otherwise \end{cases} \quad (23)$$

where $g_j(A_i)$ and $g_j(A_k)$ represent the scores of alternative A_i and A_k, respectively, with respect to the j-th criterion.

ii) The total or global concordance index $C(A_i, A_k)$ is obtained through Equation (24):

$$C(A_i, A_k) = \frac{\sum_{j=1}^{n} w_j \cdot C_j(A_i, A_k)}{\sum_{j=1}^{n} w_j} \quad (24)$$

where w_j is the weight of each criterion, defined by decision-makers.

iii) Then, the discordance index $D_j(A_i, A_k)$, for each criterion j, is defined as follows:

$$D_j(A_i, A_k) = \begin{cases} 0 & if\ g_j(A_i) > g_j(A_k) - p_j \\ 1 & if\ g_j(A_i) \le g_j(A_k) - v_j \\ \dfrac{[g_j(A_k) - g_j(A_i)] - p_j}{v_j - p_j} & otherwise \end{cases} \quad (25)$$

iv) Finally, the credibility index $\sigma(A_i, A_k)$ is calculated as follows:

$$\sigma(A_i, A_k) = C(A_i, A_k) \prod_{j \in J(A_i, A_k)} \frac{1 - D_j(A_i, A_k)}{1 - C(A_i, A_k)} \quad (26)$$

where $J(A_i, A_k) = \{j \in J\ /\ D_j(A_i, A_k) > C_j(A_i, A_k)\}$. It can be noticed that, when $D_j(A_i, A_k) = 1$, $\sigma(A_i, A_k) = 0$ since $C(A_i, A_k) < 1$.

To obtain the complete ranking of the alternatives, ELECTRE III uses a procedure deriving two complete pre-orders of the alternatives. Two ranking procedures, named “distillations”, are applied: one classifies the alternatives in descending order, from the best to the worst (descending distillation); the other one produces an ascending order, from the worst to the best alternative (ascending distillation). A final pre-order of the alternatives is then obtained as the intersection of the two complete pre-orders (Figueira et al., 2005).

Different software packages can be used to perform the described procedures of ELECTRE III, like *ELECTRE III-IV* or *Diviz*.

1.7 SHARE MCA method

SHARE MCA (SHARE project, 2012) is the MCDM method initially adopted in Aosta Valley to fully describe every river situation. It is based on the same principle of the SAW method, i.e., the additive utility assumption. However, in this case, the decision problem is organized in a hierarchical structure, similar to the framework previously described for the AHP method (shown in Supplementary Figure 1). Every criterion is detailed by one or more sub-criteria (usually called "indicators"), which convey more specific quantitative information about the effect of different alternatives. This hierarchical framework used by SHARE MCA is named "decision tree", where criteria and indicators represent the "branches" and the "leaves", respectively (Mammoliti Mochet et al., 2012).

A procedure of "hierarchical allocation of weights" is carried out in the SHARE MCA method. A weight is initially assigned to each indicator associated with a single criterion (i.e., for every group of leaves of the same branch). Afterwards, a vector of weights is allocated to criteria. Inside each group (i.e., for both the criteria and each group of indicators) the weights are normalized, i.e., their sum is equal to 1. Finally, the weight of each indicator (at the lowest level of the hierarchy) is obtained by multiplying its weight in the group of leaves and the weight of the corresponding criterion. The advantage of this kind of allocation is that the weights are assigned to homogeneous elements. Therefore, different groups of experts can work on the definition of weights linked to their own expertise. Indeed, weight allocation to each group of indicators is generally carried out by experts of the corresponding sector, while the allocation of weights to criteria is usually a political phase (Mammoliti Mochet et al., 2012).

Moreover, to compare the different indicators in a multi-dimensional decision problem, the normalization process in SHARE MCA is performed by building, for each indicator, a mathematical function that assigns to each value of the indicator a corresponding dimensionless value ranging between 0 and 1. This kind of normalization is a subjective phase since different functions can be applied to the same indicator for different case studies. Usually, the normalization functions are elaborated, for each indicator, by the corresponding group of experts involved in the decision-making process, based on their expert judgement (Mammoliti Mochet et al., 2012).

Therefore, to calculate the final performance value for the i-th alternative, $P(A_i)$, Equation (27) is used:

$$P(A_i) = \sum_{h=1}^{l} w_h \cdot n_{ih} \qquad (27)$$

where l is the number of indicators $I = \{I_h | h = 1, \dots, l\}$, w_h is the final weight of each indicator, and n_{ih} is the normalized score of alternative A_i with respect to indicator h, obtained through the normalization function.

The best alternative, for a maximization decision problem, is the one with the highest $P(A_i)$ value. The SHARE MCA method was initially implemented by using the SESAMO SHARE software (SHARE project, 2012), while more recently an online platform has been developed (SPARE project, 2018).

2 Kendall's and Spearman's non-parametric correlation tests and Borda aggregation method for the MCDM results comparison

Kendall's tau and Spearman's rho correlation tests, as well as Borda aggregation method, were performed to compare the results obtained with the different MCDM methods (excluding VIKOR and ELECTRE III, which produce a different type of ranking). They are described in the following subsections.

2.1 Kendall's tau correlation coefficient

Kendall's tau coefficient (τ) represents the similarities between two compared rankings. It is calculated through Equation (28):

$$\tau = \frac{C - D}{\frac{m(m-1)}{2}} \qquad (28)$$

where $C = \{(i,k) \mid (x_i < x_k \wedge y_i < y_k) \vee (x_i > x_k \wedge y_i > y_k)\}$ is the number of concordant pairs, $D = \{(i,k) \mid (x_i < x_k \wedge y_i > y_k) \vee (x_i > x_k \wedge y_i < y_k)\}$ is the number of discordant pair (with x and y representing two compared ranking methods, and i and k referring to two alternatives) and m is the number of alternatives.

Values of τ range from –1, for 100% negative association (completely reversed rankings), and +1 for 100% positive associations (perfect match). A value of zero indicates the absence of any association. Therefore, the higher Kendall's tau coefficient, the better is the similarity between the two compared rankings (Chauvy et al., 2020).

2.2 Spearman's rho correlation coefficient

Spearman's rank correlation coefficient (ρ) describes the degree of linear relationship between two rankings. Conceptually, it is equal to Pearson's linear correlation coefficient applied to the rankings of two measured variables, which in this case are two sets of alternatives (x and y) (Zamani-Sabzi et al., 2016). It is defined using Equation (29):

$$\rho = 1 - \frac{6 \cdot \sum_{i=1}^{m} d_i^2}{m(m^2 - 1)} \qquad (29)$$

where $d_i = x_i - y_i$ is the difference between the ranks of alternative i according to the two compared ranking methods.

The values of ρ lie between –1, indicating a strong negative correlation between the two considered rankings, and +1, denoting a perfect match between the two rankings. When the correlation coefficient is close to 0, there is a weak relation between the rankings (Ceballos et al., 2016).

2.3 Borda aggregation method

Borda aggregation method (de Borda, 1781) determines a final ranking based on pairwise comparisons among ranked alternatives in each MCDM method. In the Borda count, for each ranking, a number of points is assigned to each alternative according to its position in the ranking and these points are summed to obtain the aggregated score of the alternative. In particular, the Borda sum for the alternative A_i ($B(A_i)$) can be calculated through Equation (30):

$$B(A_i) = \sum_{k=1}^{R} m - \sigma_k(i) \qquad (30)$$

where R is the number of considered rankings (in this case the number of compared MCDM methods), m is the number of alternatives and $\sigma_k(i)$ is the ordinal position that alternative A_i has in the ranking k (Dym et al., 2002).

Therefore, for each ranking k, a value ranging between $(m-1)$ and 0 is assigned to each alternative ($m-1$ to the best alternative and 0 to the last one). Finally, the alternatives are ranked based on the values of $B(A_i)$, in decreasing order (Ehteram et al. (2018)).

3 Additional parameters defined in the case study for some MCDM methods

As explained in the manuscript (subsection 2.7.1), some of the MCDM methods considered in the study require the definition of additional parameters. In this section, the parameters defined in the case study are presented.

Supplementary Table 2, 3 and 4 show the results of the pairwise comparisons simulated by the authors, for each level of the hierarchy, based on the first scheme of weights considered in the paper, i.e., the weights defined by the stakeholders involved in the decision-making process. In the last column of each table, the weights of the compared elements calculated by the software are shown. It can be noticed that the inconsistency, directly calculated by the software, is always lower than 0.10 (see the last row); obviously, it is equal to 0 when only two elements are compared or when all the values are equal to 1.

Analogous results can be found in Supplementary Table 5, where the pairwise comparison matrix of the criteria based on the second scheme of weights, i.e., equal weights (considered for the sensitivity analysis), is represented. Pairwise comparisons for economic sub-criteria and indicators do not vary with the second scheme of weights.

Comparisons of alternatives with respect to each indicator are not illustrated because, as explained in the manuscript (subsection 2.7.1), they were performed through direct input, i.e., by introducing in the designated “direct input area” of the software the scores of the decision matrix shown in Table 3.

Supplementary Table 2. Simulated pairwise comparison between the criteria, for the first scheme of weights. The last column shows the criteria weights calculated by the SuperDecisions® software, as well as the inconsistency value (last row).

	Energy	Environment and fishing	Landscape	Economy	Weights
Energy	1	1/2	1/2	2	0.20
Environment and Fishing	2	1	1	2	0.33
Landscape	2	1	1	2	0.33
Economy	1/2	1/2	1/2	1	0.14
				Inconsistency:	0.023

Supplementary Table 3. Simulated pairwise comparison between the economic sub-criteria, for the first scheme of weights. The last column shows the sub-criteria weights calculated by the SuperDecisions® software, as well as the inconsistency value (last row).

	HP producer income	Community income	Weights
HP producer income	1	1/8	0.11
Community income	8	1	0.89
		Inconsistency:	0

Supplementary Table 4. Simulated pairwise comparison between the indicators quantifying the sub-criterion Community income, for the first scheme of weights. The last column shows the indicators' weights calculated by the SuperDecisions® software, as well as the inconsistency value (last row).

	Services (RCS)	Financial income (RC)	Criteria weights
Services (RCS)	1	1/9	0.10
Financial income (RC)	9	1	0.90
		Inconsistency:	0

Supplementary Table 5. Simulated pairwise comparison between the criteria for the second scheme of weights. The last column shows the criteria weights calculated by the SuperDecisions® software, as well as the inconsistency value (last row).

	Energy	**Environment and fishing**	**Landscape**	**Economy**	**Weights**
Energy	1	1	1	1	0.25
Environment and Fishing	1	1	1	1	0.25
Landscape	1	1	1	1	0.25
Economy	1	1	1	1	0.25
				Inconsistency:	0

For ELECTRE III, on the contrary, three thresholds (indifference, preference and veto) have to be assigned to each criterion (named “indicator” in SHARE MCA). The thresholds defined for the case study are shown in Table 3 in the manuscript, but more information about the reasons leading to these values is provided in the following lines. As explained in the manuscript (subsection 2.7.1), the thresholds were evaluated by the authors with the support of some experts and stakeholders.

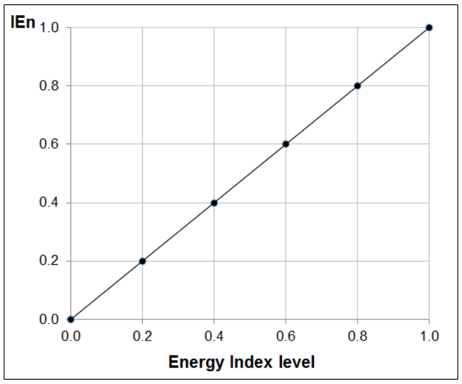
- Energy Index (IEn): the indifference threshold (q) of IEn was calculated using a hydrologic series of the Graines torrent and considering the average amount of energy produced by the HP plant in 15 days. Indeed, 15 days of downtime for an HP plant during the year are generally considered usual by HP producers (due to non-predictable failures, required maintenance operations, etc.) and the consequent losses of energy production can be considered acceptable. The corresponding value of IEn was assessed as 3.6%, which was used as the value of q. The preference threshold (p), on the contrary, was evaluated by considering the difference, in terms of average annual energy production, between two flow release scenarios, one of which (corresponding to a higher HP production) received a net preference compared to the other one. The corresponding value of IEn was assessed as 18.65% and p was set equal to this value. Finally, the veto threshold (v) was established as 0.60, based on the classification used for the Energy Index (see Supplementary Figure 2 (a)): this value corresponds to the difference between two alternatives that are in two classes of energy considered strongly different (e.g., high and poor or good and bad). The alternative with the lower value of IEn would be considered unacceptable in terms of energy production.
- Economic Index (IEc) and Financial income for the community (RC): the values of the thresholds for IEc (q = 3.5%, p = 22%, v = 0.60) and RC (q = 0.1%, p = 4.8%, v = 0.36) were obtained based on analogous considerations.
- Habitat Integrity Index (IH): the definition of the indifference threshold for IH was more complex, since the procedure for the calculation of the index, according to the MesoHABSIM method, is based on different phases, including specific surveys of representative watercourse stretches at different discharges. Therefore, an expert was involved in the assessment of the level of uncertainty associated with this procedure, according to his large experience in applying the method, and the value of q was estimated as 0.06. The p value, on the contrary, was set equal to 0.20 based on the classification of the IH scores in five classes of quality (see

Supplementary Figure 2 (b)): a difference of 0.20 between two alternatives means that they are in two different (contiguous) classes of quality and a net preference has to be given to the alternative in the higher class. Finally, the veto threshold (v = 0.30) was defined based on several simulations. The value corresponds to a difference between two alternatives considered significant enough to judge the alternative with the lower score as unacceptable for the ecological status of the watercourse. This veto may seem too low compared to the total range of the indicator score (variable between 0 and 1). However, it has to be highlighted that, generally, the range of the IH scores calculated for the same watercourse stretch in different conditions is relatively small and a difference of IH equal to 0.3 can discriminate between two very different situations.

- Landscape Protection Level (LPL): the thresholds assigned to LPL were based on similar considerations. The value of q was defined by estimating the level of uncertainty associated with the procedure for the calculation of the indicator, which can be generated by the quantification of the VEF parameter by the landscape experts. Considering that an error could occur mainly in the assessment of photos related to the months with lower discharges, in particular in summer (i.e., July and August), and taking into account the weights associated to these months in the case study (which were higher due to the increased presence of tourists in summer), this level of uncertainty, and therefore the value of q, was estimated as equal to 19.8. The values of p = 40 and v = 80 were based, again, on the classification of the LPL scores (see Supplementary Figure 2 (c)). A difference of more than 40 points between two alternatives means that they are in two different (contiguous) classes of landscape protection and a net preference has to be given to the alternative in the higher class. If the difference is higher than 80 points, the alternative with the lower score would be judged as unacceptable by the landscape experts.
- Services for the community (RCS): RCS is a true criterion since it is based on an ordinal scale. Therefore, q = p = 0. The selected value of v = 0.6 corresponds to the difference between two alternatives with a level of satisfaction, for the local community, considered strongly different, so that the lowest score would be judged as unacceptable.

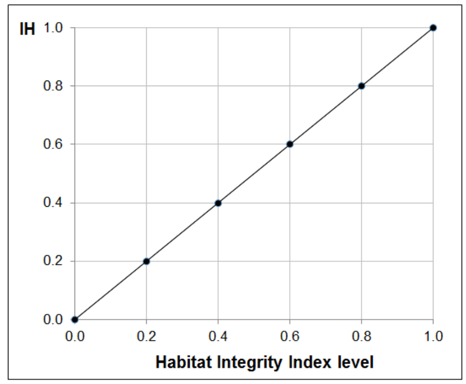
Furthermore, SHARE MCA requires the elaboration of a normalization function for each indicator. For the case study, these functions were defined during the decision-making process by the group of involved stakeholders. The normalization functions associated with the indicators IEn, IH, LPL and IEc are represented in Supplementary Figure 2, together with the corresponding classification of the indicator score. It can be noticed that all the functions are linear. For the indicators RCS and RC the normalization functions are not shown, since RCS is based on an ordinal scale, while RC is directly derived from the IEc values.

a) Energy Index



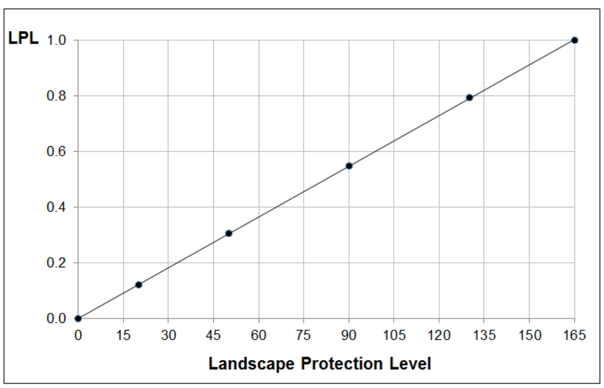
IEn	Class
0.8 ≤ IEn ≤ 1	High
0.6 ≤ IEn < 0.8	Good
0.4 ≤ IEn < 0.6	Moderate
0.2 ≤ IEn < 0.4	Poor
0 ≤ IEn < 0.2	Bad

b) Habitat Integrity Index



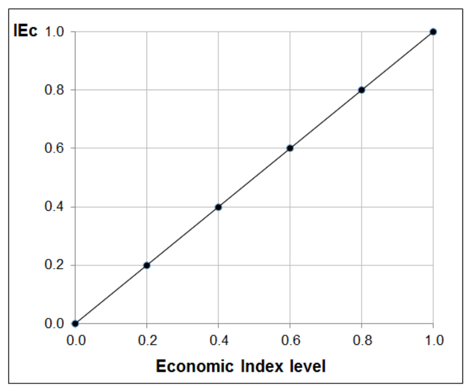
IH	Class
0.8 ≤ IH ≤ 1	High
0.6 ≤ IH < 0.8	Good
0.4 ≤ IH < 0.6	Moderate
0.2 ≤ IH < 0.4	Poor
0 ≤ IH < 0.2	Bad

c) Landscape Protection Level



LPL	Class
130 ≤ LPL ≤ 165	High
90 ≤ LPL < 130	Good
50 ≤ LPL < 90	Moderate
20 ≤ LPL < 50	Poor
0 ≤ LPL < 20	Bad

d) Economic Index



IEc	Class
0.8 ≤ IEc ≤ 1	High
0.6 ≤ IEc < 0.8	Good
0.4 ≤ IEc < 0.6	Moderate
0.2 ≤ IEc < 0.4	Poor
0 ≤ IEc < 0.2	Bad

Supplementary Figure 2. Normalization function and classification of the scores for four indicators considered in the case study: **(a)** Energy Index (IEn), **(b)** Habitat Integrity Index (IH), **(c)** Landscape Protection Level (LPL), **(d)** Economic Index (IEc).

4 Intermediate results calculated for each considered MCDM method with the first scheme of weights

4.1 Simple Additive Weighting (SAW)

The normalized and weighted normalized decision matrices calculated for the SAW method, with the first set of weights, are represented in Supplementary Table 6 and 7.

Supplementary Table 6. Normalized decision matrix computed for the SAW method.

	IEn	IH	LPL	IEc	RCS	RC
ALT 0	0.000	1.000	0.997	0.000	0.000	0.000
ALT 1	0.800	0.138	0.000	0.806	0.500	0.722
ALT 2	0.350	0.690	0.810	0.333	0.500	0.250
ALT 3	0.350	0.690	1.000	0.361	0.500	0.250
ALT 4	0.500	0.552	0.736	0.500	0.500	0.389
ALT 5	1.000	0.000	0.092	1.000	1.000	1.000
ALT 6	0.950	0.172	0.104	0.972	1.000	0.944
ALT 7	0.850	0.172	0.231	0.861	1.000	0.806
ALT 8	0.600	0.483	0.508	0.583	0.500	0.472

Supplementary Table 7. Weighted normalized decision matrix computed for the SAW method.

	IEn	IH	LPL	IEc	RCS	RC
ALT 0	0.000	0.300	0.299	0.000	0.000	0.000
ALT 1	0.200	0.041	0.000	0.012	0.004	0.092
ALT 2	0.088	0.207	0.243	0.005	0.004	0.032
ALT 3	0.088	0.207	0.300	0.005	0.004	0.032
ALT 4	0.125	0.166	0.221	0.008	0.004	0.050
ALT 5	0.250	0.000	0.028	0.015	0.007	0.128
ALT 6	0.238	0.052	0.031	0.015	0.007	0.121
ALT 7	0.213	0.052	0.069	0.013	0.007	0.103
ALT 8	0.150	0.145	0.152	0.009	0.004	0.060

4.2 Weighted Product Method (WPM)

The results of the comparisons between alternatives according to the WPM method, based on the values $R(A_k/A_l)$, for the first scheme of weights, are shown in Supplementary Table 8. The values P_i presented in the manuscript, in Table 4, were calculated through Equation (5) (see subsection 1.2), whose results confirmed the ranking obtained through the comparisons shown in the following table.

Supplementary Table 8. Comparisons between each pair of alternatives for the WPM methods, based on the ratio $\mathrm{R(ALT_k/ALT_i)}$. The values of R higher than 1 are highlighted in bold type.

	R	Comparisons
R(ALT 0/ALT 1)	**1.240**	ALT 0 ≻ ALT 1
R(ALT 0/ALT 2)	0.963	ALT 2 ≻ ALT 0
R(ALT 0/ALT 3)	0.925	ALT 3 ≻ ALT 0
R(ALT 0/ALT 4)	0.957	ALT 4 ≻ ALT 0
R(ALT 0/ALT 5)	**1.154**	ALT 0 ≻ ALT 5
R(ALT 0/ALT 6)	**1.122**	ALT 0 ≻ ALT 6
R(ALT 0/ALT 7)	**1.085**	ALT 0 ≻ ALT 7
R(ALT 0/ALT 8)	**1.004**	ALT 0 ≻ ALT 8
R(ALT 1/ALT 2)	0.777	ALT 2 ≻ ALT 1
R(ALT 1/ALT 3)	0.746	ALT 3 ≻ ALT 1
R(ALT 1/ALT 4)	0.772	ALT 4 ≻ ALT 1
R(ALT 1/ALT 5)	0.931	ALT 5 ≻ ALT 1
R(ALT 1/ALT 6)	0.905	ALT 6 ≻ ALT 1
R(ALT 1/ALT 7)	0.875	ALT 7 ≻ ALT 1
R(ALT 1/ALT 8)	0.810	ALT 8 ≻ ALT 1
R(ALT 2/ALT 3)	0.960	ALT 3 ≻ ALT 2
R(ALT 2/ALT 4)	0.994	ALT 4 ≻ ALT 2
R(ALT 2/ALT 5)	**1.199**	ALT 2 ≻ ALT 5
R(ALT 2/ALT 6)	**1.165**	ALT 2 ≻ ALT 6
R(ALT 2/ALT 7)	**1.126**	ALT 2 ≻ ALT 7
R(ALT 2/ALT 8)	**1.043**	ALT 2 ≻ ALT 8
R(ALT 3/ALT 4)	**1.035**	ALT 3 ≻ ALT 4
R(ALT 3/ALT 5)	**1.248**	ALT 3 ≻ ALT 5
R(ALT 3/ALT 6)	**1.214**	ALT 3 ≻ ALT 6
R(ALT 3/ALT 7)	**1.173**	ALT 3 ≻ ALT 7
R(ALT 3/ALT 8)	**1.086**	ALT 3 ≻ ALT 8

Supplementary Table 8. Continued.

	R	**Comparisons**
R(ALT 4/ALT 5)	**1.206**	ALT 4 $\succ$ ALT 5
R(ALT 4/ALT 6)	**1.172**	ALT 4 $\succ$ ALT 6
R(ALT 4/ALT 7)	**1.133**	ALT 4 $\succ$ ALT 7
R(ALT 4/ALT 8)	**1.049**	ALT 4 $\succ$ ALT 8
R(ALT 5/ALT 6)	0.972	ALT 6 $\succ$ ALT 5
R(ALT 5/ALT 7)	0.940	ALT 7 $\succ$ ALT 5
R(ALT 5/ALT 8)	0.870	ALT 8 $\succ$ ALT 5
R(ALT 6/ALT 7)	0.967	ALT 7 $\succ$ ALT 6
R(ALT 6/ALT 8)	0.895	ALT 8 $\succ$ ALT 6
R(ALT 7/ALT 8)	0.926	ALT 8 $\succ$ ALT 7

4.3 Analytic Hierarchy Process (AHP)

The results of the pairwise comparisons performed by the authors are shown in Supplementary Table 2, 3 and 4. Supplementary Table 9 presents the normalized scores and the aggregated weighting factors obtained for the six indicators through the SuperDecisions® software, for the first scheme of weights.

Supplementary Table 9. Normalized decision matrix according to the AHP method and aggregated weighting factors calculated for the indicators by the software SuperDecisions® (second row).

	IEn	**IH**	**LPL**	**IEc**	**RCS**	**RC**
Global weights	0.064	0.105	0.105	0.005	0.004	0.036
ALT 0	0.093	0.143	0.166	0.065	0.069	0.038
ALT 1	0.117	0.095	0.056	0.127	0.103	0.136
ALT 2	0.104	0.125	0.146	0.091	0.103	0.072
ALT 3	0.104	0.125	0.167	0.093	0.103	0.072
ALT 4	0.108	0.118	0.137	0.103	0.103	0.091
ALT 5	0.123	0.087	0.066	0.141	0.138	0.174
ALT 6	0.121	0.097	0.068	0.139	0.138	0.167
ALT 7	0.119	0.097	0.082	0.131	0.138	0.148
ALT 8	0.111	0.114	0.112	0.110	0.103	0.102

4.4 Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

Supplementary Table 10 and 11 show the normalized and weighted normalized decision matrices calculated for the TOPSIS method, with the first scheme of weights. The ideal solution (A^*) and the negative-ideal solution (A^-) are shown in Supplementary Table 12.

Supplementary Table 10. Normalized decision matrix calculated for the TOPSIS method.

	IEn	IH	LPL	IEc	RCS	RC
ALT 0	0.279	0.423	0.467	0.192	0.203	0.105
ALT 1	0.350	0.280	0.158	0.371	0.305	0.380
ALT 2	0.310	0.372	0.409	0.266	0.305	0.200
ALT 3	0.310	0.372	0.468	0.272	0.305	0.200
ALT 4	0.323	0.349	0.386	0.303	0.305	0.253
ALT 5	0.368	0.257	0.187	0.414	0.406	0.485
ALT 6	0.363	0.286	0.190	0.408	0.406	0.464
ALT 7	0.354	0.286	0.229	0.383	0.406	0.411
ALT 8	0.332	0.338	0.315	0.322	0.305	0.285

Supplementary Table 11. Weighted normalized decision matrix calculated for the TOPSIS method.

	IEn	IH	LPL	IEc	RCS	RC
ALT 0	0.070	0.127	0.140	0.003	0.001	0.013
ALT 1	0.087	0.084	0.047	0.006	0.002	0.049
ALT 2	0.078	0.112	0.123	0.004	0.002	0.026
ALT 3	0.078	0.112	0.140	0.004	0.002	0.026
ALT 4	0.081	0.105	0.116	0.005	0.002	0.032
ALT 5	0.092	0.077	0.056	0.006	0.003	0.062
ALT 6	0.091	0.086	0.057	0.006	0.003	0.059
ALT 7	0.089	0.086	0.069	0.006	0.003	0.053
ALT 8	0.083	0.101	0.095	0.005	0.002	0.036

Supplementary Table 12. Ideal solution (A^*) and the negative-ideal solution (A^-) calculated for the TOPSIS method.

	IEn	**IH**	**LPL**	**IEc**	**RCS**	**RC**
$\mathbf{A^*}$	0.092	0.127	0.140	0.006	0.003	0.062
$\mathbf{A^-}$	0.070	0.077	0.047	0.003	0.001	0.013

4.5 VIKOR

The following values were calculated for the VIKOR method, for the first scheme of weights: $S^* = 0.36$; $S^- = 0.65$; $R^* = 0.13$; $R^- = 0.30$. The check for the condition of "acceptable advantage" is represented in

Supplementary Table **13**: the difference between the second, third and fourth ranked alternatives by Q (ALT 4, ALT 2 and ALT 8, respectively) and the best alternative by Q (ALT 3) were compared with the value DQ = 0.125 to define the set of compromise solutions (first rows of the table). When the difference was below the value DQ, the alternatives were included in the set of compromise solutions (rank = 1), in addition to ALT 3. An analogous check was made for the following alternatives to establish the complete final ranking.

Supplementary Table 13. Check for the condition of "acceptable advantage" in VIKOR, with $ALT^{(1)}$ = ALT 3 and DQ = 0.125. The values highlighted in red denote that there is not an "acceptable advantage" and, therefore, the alternative is ranked in the same position as the previous one.

	$\mathbf{Q(ALT_i) - Q(ALT^{(1)})}$	**Check**	**Rank of $\mathbf{ALT_i}$**
Q(ALT 4) – Q(ALT 3)	0.026	< DQ	1
Q(ALT 2) – Q(ALT 3)	0.100	< DQ	1
Q(ALT 8) – Q(ALT 3)	0.180	> DQ	2
	$\mathbf{Q(ALT_i) - Q(ALT\ 8)}$	**Check**	**Rank of $\mathbf{ALT_i}$**
Q(ALT 0) – Q(ALT 8)	0.148	> DQ	3
	$\mathbf{Q(ALT_i) - Q(ALT\ 0)}$	**Check**	**Rank of $\mathbf{ALT_i}$**
Q(ALT 7) – Q(ALT 0)	0.244	> DQ	4
	$\mathbf{Q(ALT_i) - Q(ALT\ 7)}$	**Check**	**Rank of $\mathbf{ALT_i}$**
Q(ALT 6) – Q(ALT 7)	0.051	< DQ	4
Q(ALT 5) – Q(ALT 7)	0.206	> DQ	5
	$\mathbf{Q(ALT_i) - Q(ALT\ 5)}$	**Check**	**Rank of $\mathbf{ALT_i}$**
Q(ALT 1) – Q(ALT 5)	0.137	> DQ	6

4.6 ELECTRE III

Supplementary Table 14, 15 and 16 present the concordance matrix, the discordance matrices for each indicator (also named “criterion” in the previous references to ELECTRE III) and the final credibility matrix calculated by the J-ELECTRE software, for the first scheme of weights.

Supplementary Table 14. Concordance matrix calculated by the J-ELECTRE software.

	ALT 0	ALT 1	ALT 2	ALT 3	ALT 4	ALT 5	ALT 6	ALT 7	ALT 8
ALT 0	0	0.643	0.801	0.801	0.747	0.600	0.600	0.627	0.711
ALT 1	0.400	0	0.486	0.486	0.571	0.856	0.863	0.914	0.717
ALT 2	0.936	0.771	0	1.000	0.870	0.693	0.710	0.746	0.844
ALT 3	0.936	0.772	1.000	0	0.871	0.693	0.710	0.747	0.845
ALT 4	0.850	0.826	1.000	1.000	0	0.747	0.764	0.801	0.921
ALT 5	0.400	1.000	0.400	0.400	0.486	0	1.000	1.000	0.720
ALT 6	0.400	1.000	0.507	0.507	0.593	0.948	0	1.000	0.839
ALT 7	0.400	1.000	0.540	0.507	0.697	0.871	0.872	0	0.936
ALT 8	0.627	0.862	1.000	0.817	1.000	0.782	0.800	0.836	0

Supplementary Table 15. Discordance matrices calculated for each indicator by the J-ELECTRE software.

	IEn								
	ALT 0	**ALT 1**	**ALT 2**	**ALT 3**	**ALT 4**	**ALT 5**	**ALT 6**	**ALT 7**	**ALT 8**
ALT 0	0	0	0	0	0	0.034	0.010	0	0
ALT 1	0	0	0	0	0	0	0	0	0
ALT 2	0	0	0	0	0	0	0	0	0
ALT 3	0	0	0	0	0	0	0	0	0
ALT 4	0	0	0	0	0	0	0	0	0
ALT 5	0	0	0	0	0	0	0	0	0
ALT 6	0	0	0	0	0	0	0	0	0
ALT 7	0	0	0	0	0	0	0	0	0
ALT 8	0	0	0	0	0	0	0	0	0

Supplementary Table 15. Continued.

IH									
	ALT 0	**ALT 1**	**ALT 2**	**ALT 3**	**ALT 4**	**ALT 5**	**ALT 6**	**ALT 7**	**ALT 8**
ALT 0	0	0	0	0	0	0	0	0	0
ALT 1	0.500	0	0	0	0	0	0	0	0
ALT 2	0	0	0	0	0	0	0	0	0
ALT 3	0	0	0	0	0	0	0	0	0
ALT 4	0	0	0	0	0	0	0	0	0
ALT 5	0.900	0	0	0	0	0	0	0	0
ALT 6	0.400	0	0	0	0	0	0	0	0
ALT 7	0.400	0	0	0	0	0	0	0	0
ALT 8	0	0	0	0	0	0	0	0	0

LPL									
	ALT 0	**ALT 1**	**ALT 2**	**ALT 3**	**ALT 4**	**ALT 5**	**ALT 6**	**ALT 7**	**ALT 8**
ALT 0	0	0	0	0	0	0	0	0	0
ALT 1	0.625	0	0.320	0.630	0.200	0	0	0	0
ALT 2	0	0	0	0	0	0	0	0	0
ALT 3	0	0	0	0	0	0	0	0	0
ALT 4	0	0	0	0	0	0	0	0	0
ALT 5	0.475	0	0.170	0.480	0.050	0	0	0	0
ALT 6	0.455	0	0.150	0.460	0.030	0	0	0	0
ALT 7	0.250	0	0	0.255	0	0	0	0	0
ALT 8	0	0	0	0	0	0	0	0	0

IEc									
	ALT 0	**ALT 1**	**ALT 2**	**ALT 3**	**ALT 4**	**ALT 5**	**ALT 6**	**ALT 7**	**ALT 8**
ALT 0	0	0.184	0	0	0	0.368	0.342	0.237	0
ALT 1	0	0	0	0	0	0	0	0	0
ALT 2	0	0	0	0	0	0.053	0.026	0	0
ALT 3	0	0	0	0	0	0.026	0	0	0
ALT 4	0	0	0	0	0	0	0	0	0
ALT 5	0	0	0	0	0	0	0	0	0
ALT 6	0	0	0	0	0	0	0	0	0
ALT 7	0	0	0	0	0	0	0	0	0
ALT 8	0	0	0	0	0	0	0	0	0

Supplementary Table 15. Continued.

				RCS					
	ALT 0	**ALT 1**	**ALT 2**	**ALT 3**	**ALT 4**	**ALT 5**	**ALT 6**	**ALT 7**	**ALT 8**
ALT 0	0	0.333	0.333	0.333	0.333	0.667	0.667	0.667	0.333
ALT 1	0	0	0	0	0	0.333	0.333	0.333	0
ALT 2	0	0	0	0	0	0.333	0.333	0.333	0
ALT 3	0	0	0	0	0	0.333	0.333	0.333	0
ALT 4	0	0	0	0	0	0.333	0.333	0.333	0
ALT 5	0	0	0	0	0	0	0	0	0
ALT 6	0	0	0	0	0	0	0	0	0
ALT 7	0	0	0	0	0	0	0	0	0
ALT 8	0	0	0	0	0	0.333	0.333	0.333	0
				RC					
	ALT 0	**ALT 1**	**ALT 2**	**ALT 3**	**ALT 4**	**ALT 5**	**ALT 6**	**ALT 7**	**ALT 8**
ALT 0	0	0.680	0.135	0.135	0.295	1.000	0.936	0.776	0.391
ALT 1	0	0	0	0	0	0.167	0.103	0	0
ALT 2	0	0.391	0	0	0.006	0.712	0.647	0.487	0.103
ALT 3	0	0.391	0	0	0.006	0.712	0.647	0.487	0.103
ALT 4	0	0.231	0	0	0	0.551	0.487	0.327	0
ALT 5	0	0	0	0	0	0	0	0	0
ALT 6	0	0	0	0	0	0	0	0	0
ALT 7	0	0	0	0	0	0.071	0.006	0	0
ALT 8	0	0.135	0	0	0	0.455	0.391	0.231	0

Supplementary Table 16. Credibility matrix calculated by the J-ELECTRE software.

	ALT 0	**ALT 1**	**ALT 2**	**ALT 3**	**ALT 4**	**ALT 5**	**ALT 6**	**ALT 7**	**ALT 8**
ALT 0	0	0.578	0.801	0.801	0.747	0.000	0.080	0.336	0.711
ALT 1	0.208	0	0.486	0.349	0.571	0.856	0.863	0.914	0.717
ALT 2	0.936	0.771	0	1.000	0.870	0.652	0.710	0.746	0.844
ALT 3	0.936	0.772	1.000	0	0.871	0.652	0.710	0.747	0.845
ALT 4	0.850	0.826	1.000	1.000	0	0.747	0.764	0.801	0.921
ALT 5	0.058	1.000	0.400	0.347	0.486	0	1.000	1.000	0.720
ALT 6	0.363	1.000	0.507	0.507	0.593	0.948	0	1.000	0.839
ALT 7	0.400	1.000	0.540	0.507	0.697	0.871	0.872	0	0.936
ALT 8	0.627	0.862	1.000	0.817	1.000	0.782	0.800	0.836	0

4.7 SHARE MCA

The normalized and weighted normalized decision matrices calculated for the SHARE MCA method, with the first set of weights, are shown in Supplementary Table 17 and 18.

Supplementary Table 17. Normalized decision matrix calculated by the software SESAMO SHARE.

	IEn	IH	LPL	IEc	RCS	RC
ALT 0	0.630	0.740	0.596	0.310	0.400	0.100
ALT 1	0.790	0.490	0.202	0.600	0.600	0.360
ALT 2	0.700	0.650	0.522	0.430	0.600	0.190
ALT 3	0.700	0.650	0.597	0.440	0.600	0.190
ALT 4	0.730	0.610	0.493	0.490	0.600	0.240
ALT 5	0.830	0.450	0.238	0.670	0.800	0.460
ALT 6	0.820	0.500	0.243	0.660	0.800	0.440
ALT 7	0.800	0.500	0.293	0.620	0.800	0.390
ALT 8	0.750	0.590	0.403	0.520	0.600	0.270

Supplementary Table 18. Weighted normalized decision matrix calculated by the software SESAMO SHARE.

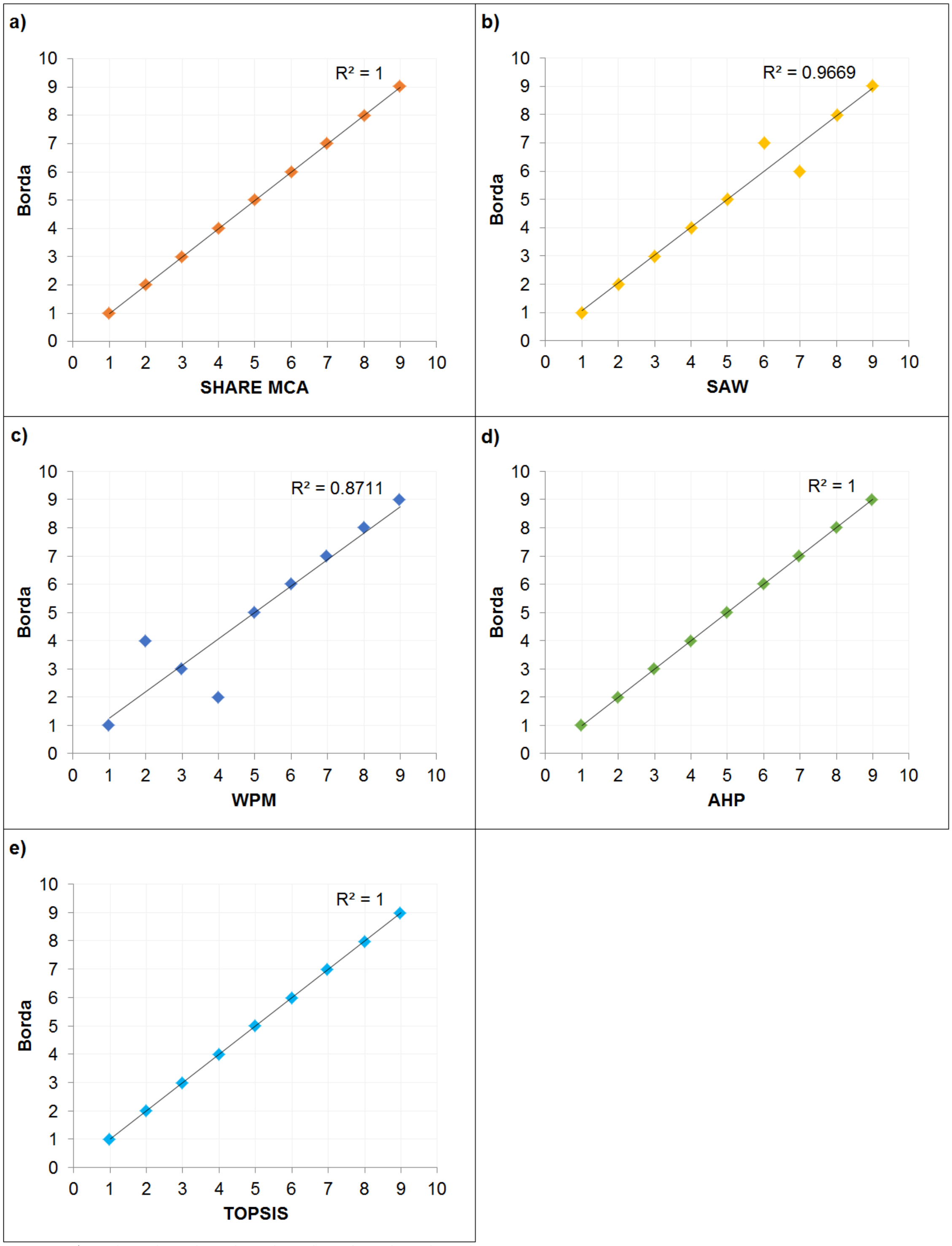
	IEn	IH	LPL	IEc	RCS	RC
ALT 0	0.158	0.222	0.179	0.005	0.003	0.013
ALT 1	0.198	0.147	0.061	0.009	0.004	0.046
ALT 2	0.175	0.195	0.157	0.006	0.004	0.024
ALT 3	0.175	0.195	0.179	0.007	0.004	0.024
ALT 4	0.183	0.183	0.148	0.007	0.004	0.031
ALT 5	0.208	0.135	0.071	0.010	0.006	0.059
ALT 6	0.205	0.150	0.073	0.010	0.006	0.056
ALT 7	0.200	0.150	0.088	0.009	0.006	0.050
ALT 8	0.188	0.177	0.121	0.008	0.004	0.035

5 Results of the Borda aggregation method

As described in the manuscript (subsection 2.4), the Borda method was used, in addition to the non-parametric correlation tests, to compare the results of the different MCDM methods. The calculation of the aggregated order through the Borda technique, for the first scheme of weights, is shown in Supplementary Table 19. The correlations between each method and the Borda order are illustrated in Supplementary Figure 3. It can be noticed that the Borda ranking is exactly the same as the order generated by SHARE MCA, AHP and TOPSIS. The results of SAW and WPM, on the contrary, slightly differ from the Borda ranking ($R^2 = 0.97$ and $R^2 = 0.87$, respectively), with two ranks switched (ranks 6 and 7 in SAW and ranks 4 and 2 in WPM).

Supplementary Table 19. Scores calculated based on the Borda method for each MCDM method, Borda sum and final aggregated ranking, for the first scheme of weights.

	SHARE MCA	SAW	WPM	AHP	TOPSIS	Borda sum	Borda ranking
ALT 0	7	7	7	7	5	33	2
ALT 1	0	0	0	0	0	0	9
ALT 2	6	6	6	6	6	30	3
ALT 3	8	8	8	8	8	40	1
ALT 4	5	5	5	5	7	27	4
ALT 5	1	1	1	1	1	5	8
ALT 6	2	3	2	2	2	11	7
ALT 7	3	2	3	3	3	14	6
ALT 8	4	4	4	4	4	20	5

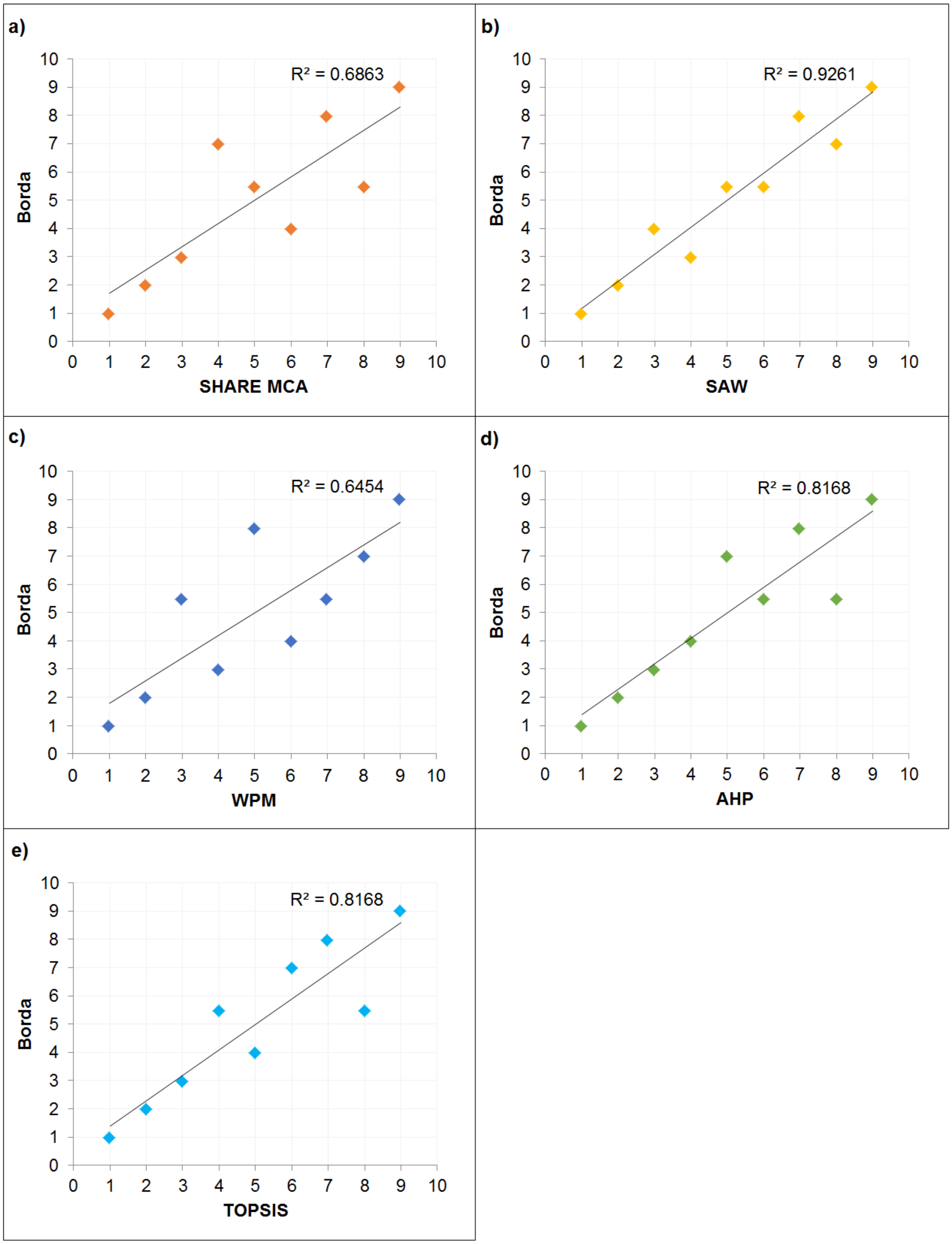


Supplementary Figure 3. Correlation between **(a)** SHARE MCA and Borda, **(b)** SAW and Borda, **(c)** WPM and Borda, **(d)** AHP and Borda, **(e)** TOPSIS and Borda, for the first scheme of weights. The values from 1 to 9 correspond to the ranks.

The same results, for the second scheme of weights, are presented in Supplementary Table 20 and Supplementary Figure 4. Looking at the graphs shown in Supplementary Figure 4, it can be noticed that SAW is the method characterized by the highest correlation with the Borda ranking ($R^2 > 0.9$). AHP and TOPSIS are also highly correlated with the Borda aggregated order ($R^2 > 0.8$, with major differences in the lowest part of the ranking). On the contrary, the results of SHARE MCA and WPM significantly differ from the Borda ranking ($R^2 < 0.7$), even if the first two ranked alternatives and the last one are always the same (also the third alternative does not change in SHARE MCA).

Supplementary Table 20. Scores calculated through the Borda method for each MCDM method, Borda sum and final aggregated ranking, for the second scheme of weights.

	SHARE MCA	**SAW**	**WPM**	**AHP**	**TOPSIS**	**Borda sum**	**Borda ranking**
ALT 0	5	1	3	4	1	14	7
ALT 1	0	0	0	0	0	0	9
ALT 2	6	5	6	6	5	28	3
ALT 3	8	8	8	8	8	40	1
ALT 4	7	7	7	7	7	35	2
ALT 5	1	4	5	3	2	15	5.5
ALT 6	3	6	4	5	3	21	4
ALT 7	2	2	2	2	4	12	8
ALT 8	4	3	1	1	6	15	5.5



Supplementary Figure 4. Correlation between **(a)** SHARE MCA and Borda, **(b)** SAW and Borda, **(c)** WPM and Borda, **(d)** AHP and Borda, **(e)** TOPSIS and Borda, for the second scheme of weights. The values from 1 to 9 correspond to the ranks.

6 Comparative analyses of the different MCDM methods' results obtained with the second scheme of weights

Kendall's tau and Spearman's rho correlation tests were performed to analyze the correlation among the obtained rankings also with the new scheme of weights (shown in Table 6 in the manuscript). VIKOR and ELECTRE III were excluded because they generate a different type of result (i.e., three rankings – by Q, S and R – and a proposed set of compromise solutions for VIKOR and a final pre-order of the alternatives characterized, in this case, by a relation of indifference between two alternatives for ELECTRE III. The results of the correlation tests for the other five MCDM methods are shown in Supplementary Table 21.

Supplementary Table 21. Numerical results of Kendall's tau and Spearman's rho correlation tests between the compared methods (excluding VIKOR and ELECTRE III), considering the second scheme of weights.

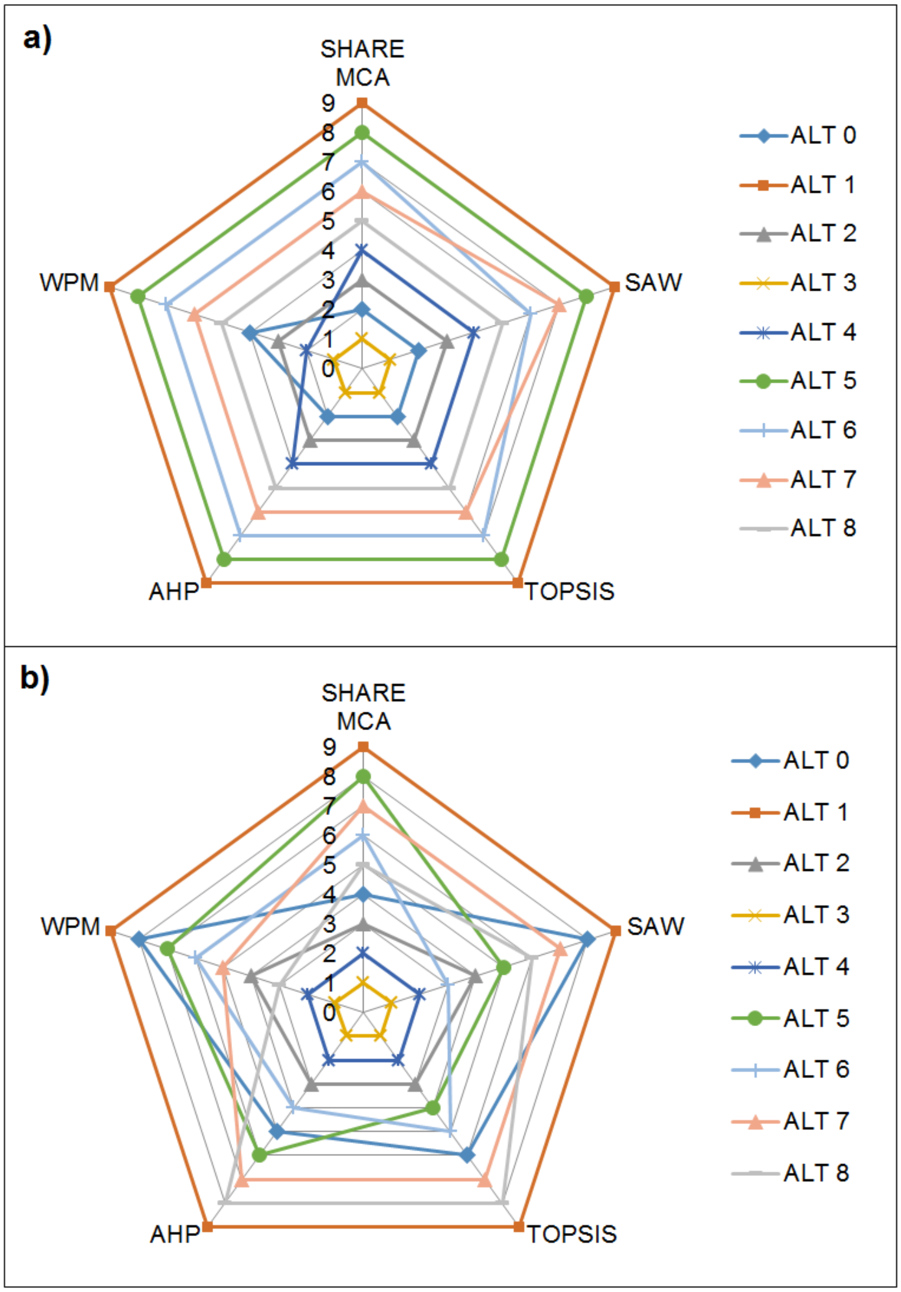
Kendall's tau coefficient					
	SHARE MCA	**SAW**	**WPM**	**AHP**	**TOPSIS**
SHARE MCA	1.000	0.556	0.667	0.722	0.611
SAW		1.000	0.667	0.722	0.722
WPM			1.000	0.500*	0.500*
AHP				1.000	0.889
TOPSIS					1.000
Spearman's rho coefficient					
	SHARE MCA	**SAW**	**WPM**	**AHP**	**TOPSIS**
SHARE MCA	1.000	0.700	0.783	0.850	0.750
SAW		1.000	0.783	0.867	0.883
WPM			1.000	0.633	0.633
AHP				1.000	0.950
TOPSIS					1.000

* Not significant correlation value (equal to the critical value)

It can be noticed that the results of both the statistic tests are significantly lower than the values calculated considering the first scheme of weights (shown in Table 5 in the manuscript). The most correlated MCDM methods are AHP and TOPSIS ($\tau = 0.889$ and $\rho = 0.950$), while WPM has the lowest correlation with the other methods (in particular with AHP and TOPSIS: $\tau = 0.5$ and $\rho = 0.633$).

It has to be highlighted that the critical value of τ in this study (i.e., for N = 9, where N is the number of ranks) is 0.5 for α = 0.05. In other words, the value of τ should be higher than 0.5 to be significant with 95% certainty. Therefore, the correlation values of WPM with AHP and TOPSIS are not significant according to the Kendall's tau test, but they are significant according to the Spearman's rho tests since the critical value of ρ (for N = 9 and α = 0.05) is 0.6.

Moreover, looking at the final rankings of alternatives generated by these five MCDM methods (presented in Table 7 in the manuscript), it can be noticed that the first two ranked alternatives are always the same (i.e., ALT 3 in the first rank and ALT 4 in the second rank), while ALT 2 is always in the third (for SHARE MCA, AHP and TOPSIS) or fourth position of the ranking (for SAW and WPM). In addition, ALT 1 is always the last ranked alternative and ALT 7 ranks seventh in all the rankings with the exception of WPM. For the other alternatives, the position in the rankings obtained with the different methods varies consistently. These differences can also be observed in Supplementary Figure 5 (b), which compares the rankings produced by the five mentioned MCDM methods, for the second scheme of weights, in a radar graph. Compared with the results obtained using the first set of weights, shown in Supplementary Figure 5 (a) and highly correlated, the differences are more evident, even if the first (ALT 3) and the last alternatives (ALT 0) remain always the same.



Supplementary Figure 5. Radar graphs comparing the different rankings obtained for SHARE MCA, SAW, WPM, AHP and TOPSIS **(a)** for the first and **(b)** for the second scheme of weights.

Furthermore, the best-ranked alternatives, i.e., ALT 3 and ALT 4, are also included in the set of compromise solutions proposed by VIKOR, in addition to ALT 8, which, on the contrary, is usually classified in the lower part of the ranking by the other methods (but it is ranked third according to WPM). Moreover, considering the ranking by Q calculated in VIKOR, the order is almost the same as the one generated by WPM: only ALT 3 and ALT 4 are switched between the first and the second rank and ALT 6 and ALT 7 are switched between the fifth and the sixth positions.

The final ranking produced by ELECTRE III, on the contrary, is significantly different from the results of the other methods. The first classified alternative is ALT 4, as in VIKOR, but it is followed by ALT 5 and ALT 6 (indifferent), which, in contrast, are ranked in the middle or lower part of the ranking by the other methods. In addition, ALT 2 only ranks sixth in ELECTRE III, while it is third or fourth according to all the other methods. Also, differently from the other methods, ALT 1 is not the last ranked alternative: it is classified second to last, followed by ALT 0.

7 Discrimination of the results for the different methods

A further analysis performed to compare the results of the seven considered MCDM methods was the evaluation of the difference between the alternatives within the produced ranking, i.e., the distance of each alternative from the best-ranked one. In particular, two percentage difference indexes were calculated, based on the performance values associated with the alternatives: D_{BW} considered the distance between the best and the worst-ranked alternatives, while D_{FS} evaluated the distance between the first and the second positions of the ranking. The results of these two indexes, for both the considered schemes of weights, are shown in Supplementary Table 22.

Supplementary Table 22. Discrimination of the results obtained with the first and the second scheme of weights for the considered methods (excluding ELECTRE III, which does not provide a performance value of the alternatives): D_{BW} = percentage difference between the best and the worst-ranked alternatives; D_{FS} = percentage difference between the first and the second positions of the ranking.

First scheme of weights						
	SHARE MCA	**SAW**	**WPM**	**AHP**	**TOPSIS**	**VIKOR**
D_{BW} (%)	-20.51%	-45.00%	-25.44%	-28.27%	-60.32%	1081.54%
D_{FS} (%)	-0.97%	-5.70%	-3.41%	-0.88%	-5.80%	30.74%
Second scheme of weights						
	SHARE MCA	**SAW**	**WPM**	**AHP**	**TOPSIS**	**VIKOR**
D_{BW} (%)	-13.92%	-28.25%	-15.39%	-15.34%	-28.01%	926.20%
D_{FS} (%)	-3.04%	-5.16%	-0.08%	-3.40%	-4.28%	41.10%

Looking at the table, it can be noticed that high discrimination of the results is ensured by TOPSIS and SAW, especially considering the first scheme of weights. SHARE MCA and AHP (with the first scheme of weights) and WPM (with the second set of weights), on the contrary, show relatively low discrimination of the results, with very close performance values for the first and the second-ranked alternatives.

The indexes presented for VIKOR were calculated considering the ranking by Q (from which the final ranking of the alternatives was obtained). Differently from the other methods, in this case, the alternatives are ranked in decreasing order (indeed, the best alternative is the one with the minimum value of Q): for this reason both the indexes are positive, since there is an increase between the first ranked alternative (by Q) and the following ones. However, this method shows very high discrimination of the results (for example, the percentage increase between the first and the second alternatives is higher than 30%). Moreover, it has to be highlighted that the final step of VIKOR already includes a check for the condition of "acceptable advantage" to define the compromise solution(s), considering the value $DQ = 1/(m-1)$: if the first ranked alternative (by Q) does not have an "acceptable advantage" on the following one, all the alternatives for which the relation $Q\left(A^{(k)}\right) - Q\left(A^{(1)}\right) < DQ$ is valid are included in the set of compromise solutions (together with the first alternative).

Finally, the indexes were not calculated for ELECTRE III, since the method does not provide a performance value for the alternatives, but only an ordinal rank. However, it has to be noticed that the final pre-order of ELECTRE III identifies the presence of alternatives which resulted indifferent after the procedure of descending and ascending distillations and assigns them the same rank.

8 Strengths and weaknesses of the seven considered MCDM methods

Based on the comparative evaluation of the considered MCDM methods (summarized in Table 8 in the manuscript), the main observed strengths and weaknesses of each method were collected. They are presented in Supplementary Table 23.

Supplementary Table 23. Summary of the strengths and weaknesses of the different MCDM methods.

	Strengths	**Limitations**
SHARE MCA	- Simple procedure, based on the same additive principle of SAW; - Quite easy to understand, also for practitioners; - The hierarchical framework ("decision tree") allows the breakdown of even complex problems and facilitated the allocation of weights; - Results are aligned with expert-based assessment; - No need for complex computer programs.	- Need for a set of normalization functions, one for each indicator; - Subjectivity linked to the selection of the normalization functions.

Supplementary Table 23. Continued.

	Strengths	Limitations
SAW	- Simple calculation; - No need for complex computer programs[1, 2]; - Intuitive to decision-makers and well-known by practitioners [3]; - Possibility to compensate among criteria [1].	- Difficulties when it is applied to multi-dimensional MCDM problems: need for normalization [4]; - Results do not always reflect the real situation [1].
WPM	- Easy to use with multi-dimensional MCDM problems [4]; - The different units of measure are automatically removed by ratios [3, 5]; - No need for normalization (if all the criteria are of the same type, i.e., benefit or cost) [5]; - No need for complex computer programs.	- "Practitioner-unattractive" mathematical concept (even if the formulation is simple) [3]; - Possible difficulties when some alternatives have very different scores for a criterion (the ranking of alternatives tends to be too much conditioned by that criterion [5].
AHP	- The hierarchy structure can fit different sized problems [1]; - It allows the breakdown of complex problems [6]; - Pairwise comparisons facilitate the assignment of preferences by decision-makers [7]; - Pairwise comparisons allow managing both qualitative and quantitative data [8].	- High number of pairwise comparisons required for large scale problems [7]; - Possible inconsistencies of the judgements provided by the decision-maker(s) [1]; - Restrictions to the number of criteria (and alternatives) to be compared, to avoid inconsistency of judgements (less than nine) [9]; - High level of subjectivity and uncertainty due to the decision-makers' pairwise comparisons [8]; - Need for a software program to calculate the overall performance values of the alternatives.
TOPSIS	- Simple procedure, easy to understand (also for practitioners) [1, 3]; - Quick process, not requiring the definition of additional parameters by decision-maker(s) [5]; - No need for complex programs (a simple spreadsheet can be used).	- The use of Euclidean Distance does not consider the correlation of criteria [1]; - Difficult to keep the consistency of judgments [1].

Supplementary Table 23. Continued.

	Strengths	Limitations
VIKOR	- Quite easy to understand, also for practitioners; - Quick process, only requiring the definition of the υ parameter by decision-maker(s) [5]; - No need for complex programs (a simple spreadsheet can be used); - In addition to ranking, it proposes compromise solutions (one or a set), thus helping decision-makers to reach a final decision [10]; - It checks the acceptability of the obtained results (“acceptable advantage” and “acceptable stability in decision-making”) [5].	- A complete ranking of the alternatives may not be achieved [11].
ELECTRE III	- Suitable for decision problems involving non-homogeneous variables and different types of criteria [5]; - It can deal with uncertainty, imprecision and ill-determination of data, through the threshold approach [1, 2, 12]; - No need for normalization, since it can also handle ordinal or descriptive information [3]; - The outranking concept seems relevant to practical situations [3]; - Very poor performance on a single criterion may exclude an alternative from consideration [7].	- Algorithm used is relatively complex [7]; - Both the process and outcome can be difficult to explain in layman’s terms [1]: it could be perceived as a “black box” by practitioners; - Difficulties linked to the definition of realistic threshold values [2,13]; - Subjectivity and possibility of error linked to the choice of thresholds; - Need for a software package, which may decrease the level of confidence of decision-maker(s); - Difficulty to identify strengths and weaknesses of the alternatives due to outranking [1]; - It does not define how much one alternative is better than another one since no performance values are calculated (only ordinal ranks); - Possible presence of relations of incomparability between the alternatives, which can generate an equivocal final ranking; - A complete ranking of the alternatives may not be achieved [3, 7].

[1] Velasquez and Hester, 2013; [2] Frijns et al., 2015; [3] Zanakis et al., 1998; [4] Triantaphyllou and Baig, 2005; [5] Caterino et al., 2009; [6] Altunok et al., 2010; [7] Hodgett, 2016; [8] Dotoli et al., 2020; [9] Lima Junior et al., 2014; [10] Opricović and Tzeng, 2004; [11] Zamani-Sabzi et al., 2016; [12] Figueira et al., 2005; [13] Saracoglu, 2015.

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