Environmental and Sustainability Indicators 23 (2024) 100453

Contents lists available at ScienceDirect

Environmental and Sustainability Indicators

journal homepage: www.sciencedirect.com/journal/environmental-and-sustainability-indicators

A sensitivity analysis of composite indicators: Min/max thresholds

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A R T I C L E I N F O

Keywords:
Composite indicator
Sensitivity analysis
Scoring function
Min/max thresholds
Rank reversal
Implicit weighting

A B S T R A C T

The aim of composite indicators is to express the overall performance of countries/regions with respect to a complex goal including sustainability, competitiveness, and innovation. Some of the indices play an important role in real governmental and strategic decisions on allocating sources. Sensitivity analyses usually include the changes in weights (of importance), the evaluations with respect to the criteria and the aggregating functions. In contrast, we investigate the effect of setting the minimal and maximal thresholds of the scoring functions used in the assessment. Thus, only the effect of this transformation is investigated, while the input data and criteria weights are not modified or stochastic. It is demonstrated that even such a seemingly innocent modification of the min/max thresholds might lead to remarkable changes in the ranking. Results are presented in detail on the examples of the Environmental Performance Index (EPI) and the Digital Economy and Society Index (DESI). However, the phenomenon is general: further 15 composite indices, applying the min/max threshold, have also been collected. The choice of min/max threshold is functionating as an implicit (re-)weighting of the criteria: criteria with smaller min/max ranges are overweighted. Thus, the steps of weighting and assessment are not independent. This research provides an alternative sensitivity analysis to test the robustness of the rankings.

1. Introduction

Composite Indicators (CIs) draw significant attention in today's rapidly changing world, as they are considered valuable tools in measuring complex processes. Due to their simplistic design and the clear messages that they convey (Sébastiena and Bauler, 2013), a huge variety (Nardo et al., 2008; Hontoria et al., 2023; Bandura, 2011) were created and are heavily used worldwide in prioritizing policies, monitoring performance, and communication (JRC & OECD, 2008).

Their adoption by global institutions such as EC, OECD, WB, and WEF (Saltelli, 2007) has further captured the attention of the media and policymakers around the world (Greco et al., 2019). Furthermore, according to the findings of Saisana and Tarantola (2002), (2005) statistical offices and national or international organizations are utilizing CIs more and more to communicate details about the condition of countries across various areas, such as the environment, economy, society, and technological advancement. Energy efficiency (Dolge et al., 2020) and security (Shu et al., 2021) also are subject to be measured by composite indices.

Nevertheless, besides the vast number of positive reactions CIs received from various sources, they also pose a few challenges. According to Nardo et al. (2005) developing a composite indicator is not straightforward, and there are several methodological obstacles that pose technical difficulties. Inadequate handling of these issues can result in misinterpretation or manipulation of composite indicators. Hence, it is crucial to construct and use them with utmost care and attention. CIs

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https://doi.org/10.1016/j.indic.2024.100453
Received 27 February 2024; Received in revised form 4 August 2024; Accepted 4 August 2024
Available online 6 August 2024

need special treatment, uncertainty, and sensitivity analysis to increase their transparency, primarily since they are heavily used for resource allocation, elaboration of national strategies, monitoring transformation, development, and the overall performance of countries.

The European Council also uses the performance of the Member Countries with CIs. In particular, Digital Economy and Society Index (DESI) is used to monitor the overall digital performance of the EU Member States and to improve their digitalization, as the Recovery and Resilience Facility allocates approximately €127 billion towards digital reforms and investments, presenting a unique opportunity for the acceleration of digital transformation (European Council, 2022). Moreover, the Environmental Performance Index (EPI) is mentioned in the 20-year strategic plan (2017–2036) for the Ministry of Natural Resources and Environment in Thailand (Punyaporn et al., 2021); other ten CIs used in various policy areas are presented in the article of Pichon et al. (2021). According to their findings, in the realm of policymaking, evidence and data play a pivotal role, especially in the creation of foresight reports, prioritization, mitigation of adverse effects, and identification of optimal trade-offs. To mention some instances, in Hungary the Digital Economy and Society Index (DESI, 2022) was used to elaborate the national digital strategy for 2012–2030. Moreover, the Summary Innovation index from European Innovation Scoreboard (2021) had an influence on the Hungarian Research, development, and innovation strategy 2021–2030. In Romania, the E-Government Development Index (2022) was used in the elaboration of National Strategy on Digital Agenda 2020; MSI and Informationala, 2015). Furthermore, the GINI index and SDGs (Statista, 2020) are used in the elaboration of the National Strategy for sustainable development 2030 (Paideia, 2018), and DESI is used in Digital Education strategy (MEC, 2020). Appropriately utilized, indicators can provide a foundation for enhanced regulatory measures.

The creation of composite indicators (CIs) demands the provision of genuine information, a responsible approach to their development, and employment of highly precise methodologies. The challenges posed by CI construction have garnered significant academic attention, with 11507 results from WoS core collection relating to CIs. It is crucial not only to construct CIs with care, but also to interpret them correctly to prevent the dissemination of inaccurate information (Freudenberg, 2003).

Our research provides a methodological examination of CIs, with a particular focus on highlighting the significance of sensitivity analysis concerning evaluation (scoring) functions. In particular, we consider the impact of adjusting the minimum and maximum thresholds within scoring functions, while keeping every other aspect (criteria weights, input data, and aggregation methods) the same. Despite the prevailing tendency to assess ranking sensitivity independently of scoring functions, our aim is to emphasize its integral role by demonstrating its parity with other influential factors in our analysis.

The remainder of the paper is structured as follows. Section 2 provides a summary of the related literature with special attention to the goals and types of composite indicators (Subsection 2.1), methodological questions and critiques (Subsection 2.2), and problems connected to sensitivity analysis (Subsection 2.3). Section 3 presents the data and the applied methodology, while Section 4 contains the main results of the paper. The study demonstrates, via the Environmental Performance Index, where we investigate whether the choice of thresholds induces an implicit weighting. Section 5 includes another detailed example, the Digital Economy and Society Index, while Section 6 details further 15 composite indices having min/max thresholds in their methodology. They are potential 'victims' of the min/max threshold phenomenon, too. Finally, Section 7 concludes and raises further related research questions.

2. Literature review

2.1. Composite indicators –types and goals

Composite indicators are widely used, according to the European Council (2022) the interest in CIs is coming from the fact that they are like mathematical computational models, and the justification for a composite indicator determined by its suitability for the intended use and the acceptance of peers (Rosen, 1991). The rapid pace at which society is transforming requires an equal speed in identifying issues and correcting course (Euroabstracts, 2003; Nardo et al., 2005). CIs are a useful tool and are acknowledged for their 'ability to integrate large amounts of information into easily understood formats for a general audience' (JRC & OECD, 2008) and are 'much easier to interpret than trying to find a common trend in many single indicators' (Singh et al., 2009).

JRC and OECD (2008) define three levels of indicator groupings: individual, thematic (individual indicators grouped around a specific area), and composite indicators (thematic indicators compiled into a synthetic index – a single composite measure). According to JRC and OECD (2008), when conducting policy analysis at the national and international levels, indicators prove beneficial in detecting patterns in policies and performance, and highlighting specific concerns.

CIs are used 'to measure complex and multidimensional concepts' (Becker, 2022) that cannot be described by a single variable. CIs synthetize multiple (tens or even hundreds of) sub-indicators with the aim of providing a general picture of a complex system that can be used for further analysis, reporting, policy recommendations. Sébastiena and Bauler (2013) published a study on the significance of CIs for policy-making.

Due to their simplicity, CIs could bolster even further the case for their implementation in several practices (Greco et al., 2019). CIs are considered valuable tools for policymakers and decision-makers because they give insights into the direction of development; they can be used to compare situations, countries, or regions, and they can be used to evaluate the performance toward goals and targets. Moreover, they are powerful in identifying action items and anticipating future conditions and trends. They are also an efficient way to align and communicate with decision-makers and the public. CIs are often characterized as easily interpretable as they provide clear signals. Due to their seemingly uncomplicated structure and unambiguous messaging, composites are expected to influence both high-level policymakers and the broader public/stakeholder community (Sébastiena and Bauler, 2013). CIs are particularly powerful in complex fields, like innovation, competitiveness, or poverty, where it's hard to measure a society's performance otherwise (Saisana, 2014). According to Saltelli (2007), the composite indicators 'are helpful in benchmarking country performance'. CIs offer straightforward unit comparisons that can effectively illustrate the complexity of our dynamic environment in wide-ranging fields (Nardo et al., 2008). According to Freudenberg (2003), CIs are increasingly widely recognized as policy making and public communication tools. The aim is to share information on countries' performance in fields such as environment, economy, society, and technological development. CIs can serve as a valuable tool for benchmarking countries, and when assessed periodically, they can indicate the progress or direction of change over time, thus contributing to policy-making efforts (JRC & OECD, 2008).

CIs are applied in different dimensions of reality, for instance, to measure a country's competitiveness (Schwab, GCI, 2019; Schwab and Zahidi, 2020), innovativeness (Es-Sadki and Hollanders, 2021), eco-innovation (EC, 2021), sustainable development (Sachs et al., 2020), and the rule of law index (WJP, 2021). The measurement of multidimensional concepts like innovative capacity of countries, competitiveness of economies, e-government development level, and sustainability of development requires a broad approach and many indicators. Weighted criteria themselves might serve as a decision support tool in strategy making (Srdjevic and Lakicevic, 2023) and procurement (Rodriguez et al., 2021). CIs are developed continuously for different economic performances and policy areas (JRC & OECD, 2008). There are widely used indicators for the assess of *economy:* Doing Business Indicators (The World Bank, 2021); *environment:* Quality of Air Index (IQAir, 2020), Environmental Performance Index (2022), Living Planet Index (Almond and WWF, 2020); *globalization* (KOF and Institute, 2022)*:* World Competitiveness Index (IMD, 2022), the Globalization Index (2022), Global Competitiveness Index (2020); *innovation-technology:* Summary Innovation Index, European Innovation Scoreboard (Es-Sadki and Hollanders, 2021), The Networked Readiness Index (Dutta and Lanvin, 2020), e-Government Development Index (2022); and *society:* Social progress index (2020), Human Development Index (2022), Wellbeing (OECD, 2020).

Due to CIs' ability to condense the complexity of our environment, their adoption worldwide is rapidly growing (Paruolo et al., 2013). In 2006, Bandura cited more than 160 composite indicators (Bandura, 2006), later, in 2011 she identified over 400 official CIs (Bandura, 2011). In 2014, Lin Yang presented 101 composite measures of human well-being and progress built upon the first HDI published in 1990 (Yang, 2014). In 2021, European Parliament Research Service published an analysis of ten selected CIs describing their objectives in publishing the index, the data compiled, and their actual and potential use by policymakers (Pichon et al., 2021). Therefore, their proper use and the credibility of their results are of paramount importance.

2.2. Methodological questions and critiques

Like all metrics, CIs are designed to quantify as realistically and accurately as possible. Although each composite indicator is built in a logical way, the rationale behind can be different (Gatto and Drago, 2020). Consequently, the indices themselves can also lead to seemingly contradictory results. According to Nardo et al. (2005) the CIs are formed by mathematically combining individual indicators that represent various aspects of a concept, which is the focus of the analysis. CIs integrate many specific indicators; i.e., quantitative and qualitative measures (JRC & OECD, 2008). It is possible to compute them in areas that can or cannot be empirically tested (sustainable development index, innovation) (Freudenberg, 2003). A CI is an aggregated index comprising individual indicators and weights that commonly represent the relative importance of each indicator (Nardo et al., 2005). The definition 'Composite Indicators are based on sub-indicators that have no common meaningful unit of measurement, and there is no obvious way of weighting these sub-indicators' was presented in 2002 at the Inter-service consultation meeting of EC, held in Brussels (Saisana and Tarantola, 2002). According to Becker (2022) CIs usually employ a hierarchical structure which breaks the concept down into its constituent elements or dimensions, also known as sub-pillars, pillars, sub-indexes. According to Saisana and Tarantola (2002) science cannot offer an entirely objective approach to creating a definitive composite indicator that accurately summarizes a complex system. However, scientific methods can greatly assist in ensuring that the process of aggregation is conducted in a rigorous and transparent manner (In this respect, (EC, COM(2001) 619 final, 2001) can be consulted).

JRC and OECD (2008) underline that when CIs are used to measure countries' performance and compare over time, the indexes can be deceptive. Due to methodological difficulties of measuring complex economic problems, CIs can be easily manipulated to achieve a desirable outcome. If CIs are not adequately constructed and interpreted, they can lead to too simplistic analytical or policy conclusions. In fact, they must be used as a means of initiating debate and arousing public interest and must be interpret in the relevant field to the CI. Furthermore, official statisticians often criticize CIs, as thorough research is lost or hidden behind the single number output. However, according to Saisana et al. (2005), stakeholders and practitioners still use them to summarize complex or even exclusive problems. These single figures have to be used with caution to benchmark country performance for policy consumption. For pros and cons see: (Saisana and Tarantola, 2002; Nardo

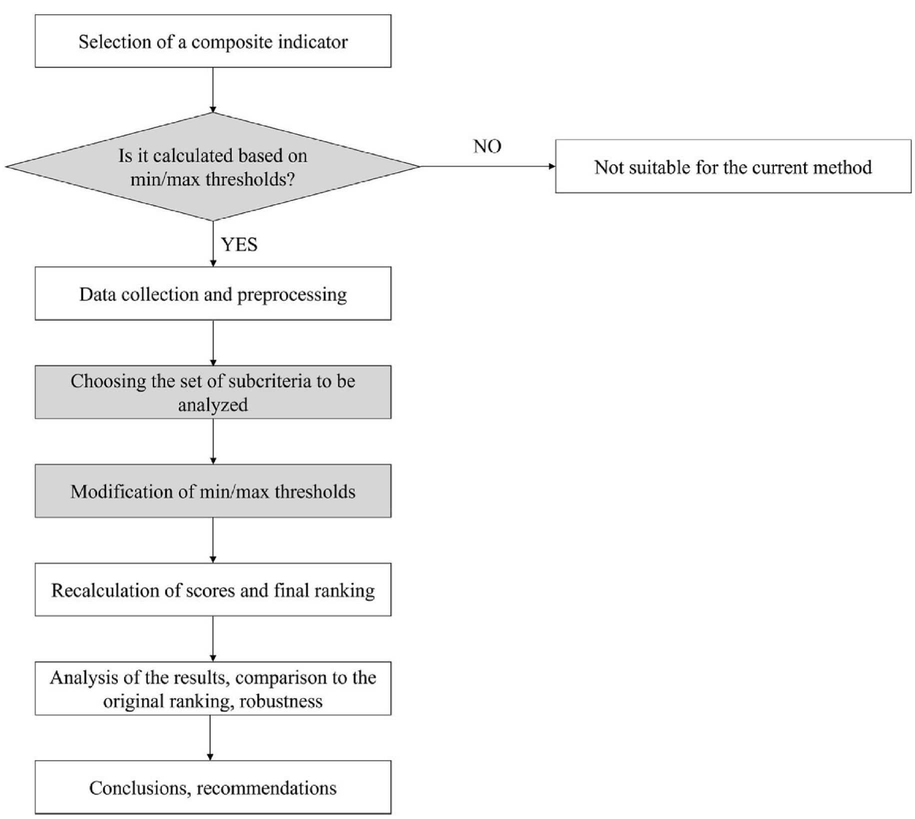

Fig. 1. The steps of the sensitivity analysis proposed by the authors.

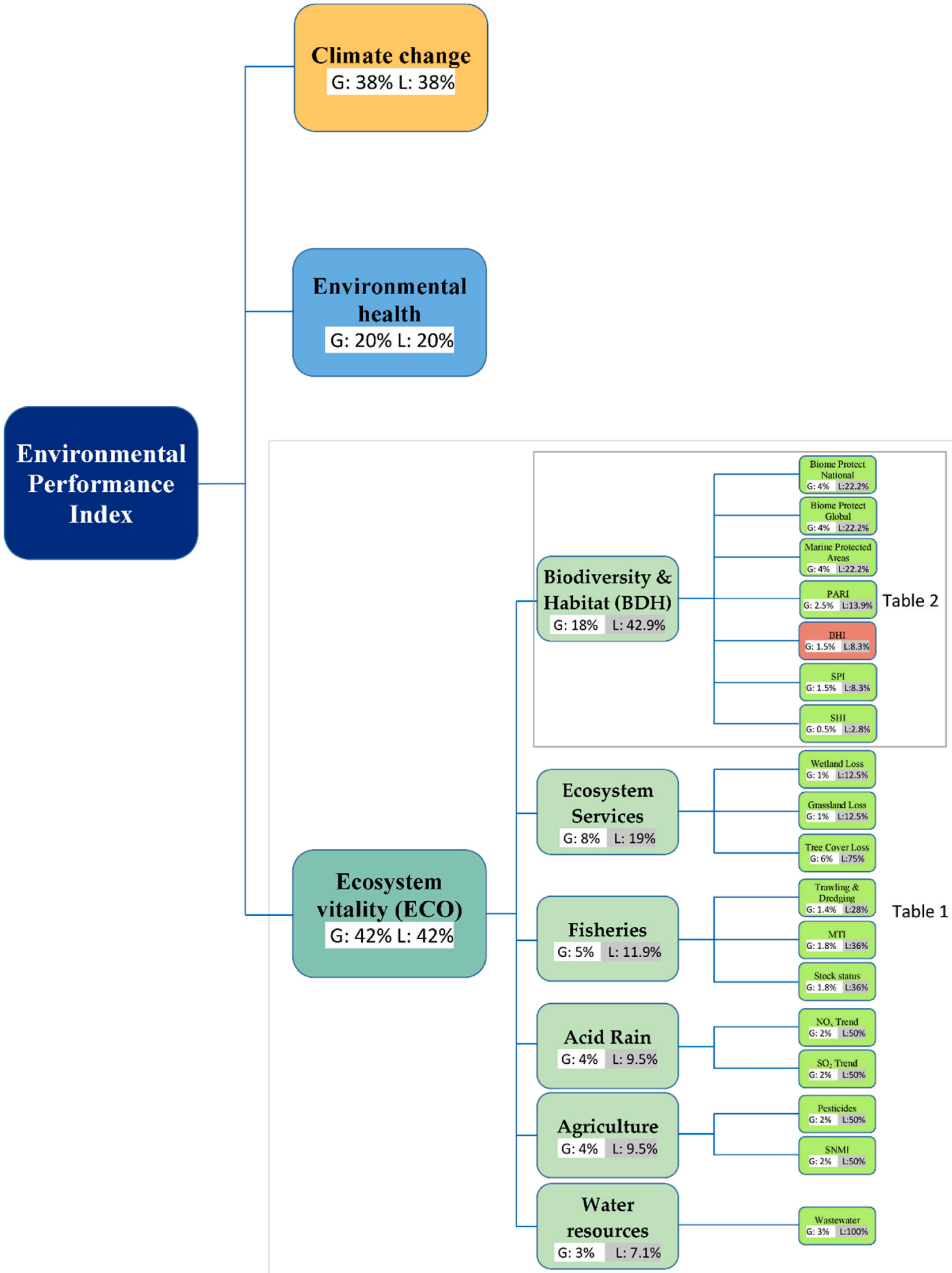

Fig. 2. Criteria tree of EPI. Data sourced from 2022 EPI, edited by the authors (Wendling et al., 2022).

et al., 2005; Saltelli, 2007).

As a result of the outstanding popularity on the one hand and extensive criticism on the other, composite indicators' raised the researchers' interest, leading to the analysis of their methodology (Greco et al., 2019; Becker et al., 2017). Many methodologies have been developed to construct CIs, see (Gibari et al., 2018; Nardo et al., 2005, 2008). Nardo et al. (2005) present a detailed description of a CI, from construction to overcoming obstacles: the statistical treatment of the set of indicators (multivariate analysis, imputation of missing data and normalization techniques), the weighting and aggregation procedures, uncertainty, and sensitivity analysis.

The JRC (Joint Research Centre) started working on composite indicators in 2002 and published a handbook with OECD in 2008 (JRC & OECD, 2008) that became a reference book for constructing CIs in various fields. In 2016, the EC launched the Competence Centre on Composite indicators and Scoreboards (JRC-COIN) (EC, 2022a,b,c). The JRC-COIN developed methodologies for constructing robust CIs and made more than 100 statistical audits (for example, EPI (Wendling et al., 2022), GII et al. (2020), GCI (Schwab & Zahidi, weforum.org, 2020). The JRC-COIN mission is 'to contribute to better monitor the impact of EU strategies & policies at national, regional and local levels by developing and auditing composite indicators and scoreboards summarizing multidimensional concepts' (EC, 2022a,b,c).

2.3. Problems connected to sensitivity analysis

Greco et al. (2019) provides a survey on the methodological aspects of composite indicators, particularly on the weighting and aggregation steps. Nardo (2005) introduces and present methods (for example variance-based methods) able to measure CI sensitivity in terms of the contribution of each factor involved in the CI construction on its variability. Davino and Romano (2014a,b) propose an ANOVA and PCA based assessment of composite indicators, where they take into account the external information as well (data transformation, weighting method, aggregation method, etc.). Dobbie (2013) study the robustness and sensitivity of weighting and aggregation, which is one of the most important steps to create a composite index, by simulation.

Kovacevic and Aguña (2010) study the Human Development Index and refer to the choice of functional form and normalization as implicit weighting. They attribute a share of the total output uncertainty to the inputs, namely the minimum goalposts, functional forms and weights.

The changes in criteria's weights are investigated by Butler et al. (1997) according to whom the effect of the modification of a single criterion's weight or that of two criteria to the ranking is tracked by linear inequalities; while a simulation is used in case of a larger number of modified weights. Statistical analysis of possible rankings is calculated from random weights with and without ordinal constraints on the criteria's importance.

Triantaphyllou and Sánchez (1997) consider the changes in weight and the evaluations of the alternatives with respect to the criteria, however, these changes are not simultaneous. Mészáros and Rapcsák (1996) focus on a general sensitivity problem: weights, evaluations, and even voting powers of decision-makers are allowed to change simultaneously, and the rank reversal of any pair of alternatives can be added to the set of constraints to find the maximal level of uncertainty without prescribed rank reversal. The implicit weighting induced by the choice of aggregation and normalization methods is investigated in detail by Prado (2020).

Sensitivity analyses above include the changes in weights (of importance), the evaluations with respect to the criteria and the aggregating function. Uncertainty in the input data is often simulated, by the addition of randomly generated noise (Gatto and Drago, 2020; Drago and Gatto, 2022a, 2022b). Statistical analysis show how the total scores vary, what are the maximal/minimal values attended, and also that how robust the original ranking is. The interval-based approach makes the robustness of the composite index visible and measurable. Full rankings are typically unstable, in particular when the simultaneous changes of many or all input data is allowed. However, some positions or relations among certain (set of) alternatives may be robust even if the whole ranking itself is sensitive. Such information help the decision makers estimating the degree of reliability of the composite index applied.

Our research follows a different approach. Input data and aggregation functions are considered fixed, there is no uncertainty investigated in these regards, thus the method of simulations cannot be applied. However, since there is still some freedom in the setting of scoring functions, and the ranking is influenced by this choice. The effect of changing the minimal and maximal thresholds of the scoring functions is investigated. In spite of the fact that sensitivity of ranking is often examined without considering the scoring functions, we would like to demonstrate that they are as important as other factors. The choice of minimal and maximal thresholds of the scoring functions functionates as an implicit (re-)weighting of the criteria. When the weights of criteria are determined, decision makers are not necessarily aware of how min/max thresholds would influence the scores.

3. Methodology and data

The new approach of the process of sensitivity analysis is shown in Fig. 1. The steps are similar to any other sensitivity tests, but the deviations compared to other sensitivity analyses illustrated in Appendix A are shown in grey. The calculation used by the authors is suitable for indices that are scored with min/max thresholds. The effect of changing these limits is then examined. In addition, when using the current method, it is recommended to select one or more performance indicators, but the effect of changing all of them can also be studied.

To exemplify the general phenomenon of the importance of the scoring functions in the final ranking, this paper the Environment Performance Index (EPI), in particular the Ecosystem Vitality (ECO) criterion and its sub-criteria. EPI can be used to illustrate our example because its detailed data and calculation method are published and simply accessible (Wendling et al., 2022) so that the results can be reproduced and further analyzed. This nature of EPI also contributed to the fact that it has been extended and generalised several ways, (e.g., applying it on provincial level (Zuo et al., 2017)) as well as used as an example for different methodological studies (Rogge, 2012). In terms of the sensitivity analysis of the index, the stochastic methods dominate the literature (Saisana and Saltelli, 2010; Pinar, 2022), and the weights of the different criteria are studied rigorously, meanwhile the focus of our research, the scoring functions, especially their min/max thresholds are

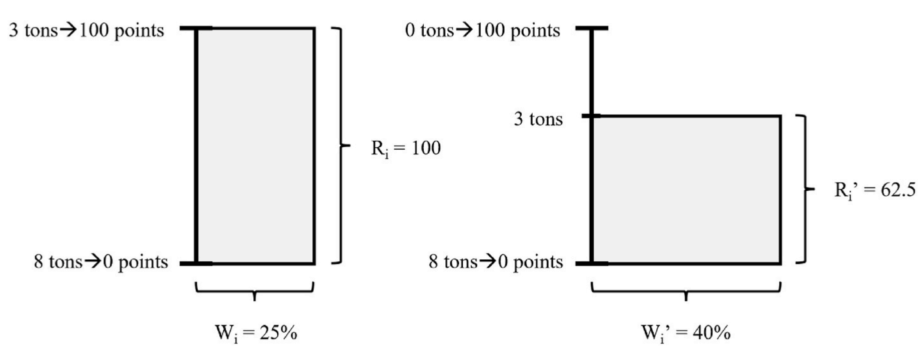

Fig. 3. Weighted scores (rectangles' areas): 8-3 = 5 tons difference in CO2 emission (smaller the better) results in 0.25*100 = 25 points difference between two actors (left); changing the maximal score at 0 tons, the same score difference can be achieved with larger weight, 0.4*62.5 = 25 (right).

Table 1
A non-exhaustive list of composite indices using min/max thresholds in their scoring methodology.

Index	Number of main criteria	Number of leaf criteria	Source
DBI: Doing Business indicator	11	11	The World Bank (2021)
DESI: Digital Economy and Society Index	4	33	EC and Commission (2022) p. 10
Eco-IS: Eco-innovaton Action plan	5	12	EC (2022b) p. 5
EIS: European Innovation Scoreboard (former Summary Innovation Index)	12	32	EC (2023) p. 21
EPI: Environmental Performance Index	3	40	Wolf et al. (2022) p. 158
GCI: Global Competitiveness Index	12	103	The World Economic Forum (2023) p. 7
GI: Globalization index	6	43	Gygli et al. (2019) p. 1
GII: Global Innovation Index	7	80	WIPO (2023) p. 217
GovAI RI: Government AI Readiness Index	3	39	Oxford Insights (2023) p. 42
HDI: Human Development Index	3	4	Human Developmennt Report Office (1994) p. 7
IDI: ICT Development Index	2	10	ITU (2023) p. 25
IEF: Index of Economy Freedom	4	≤242	The Heritage Foundation (2023) pp. 403-409
NRI: Networked Readiness Index (former Global Information Technology Report)	4	58	Portulans Institute (2023) p. 222
PI: Prosperity Index	3	300	Legatum Institute (2023) p. 9
RW: Regional Well-Being	3	13	OECD (2022)
SDG: Sustainable Development Goals Index	17	97 (+27 for OECD)	Sachs et al. (2023) p. 97
SPI: Social Progress Index	3	57	Stern et al. (2024) p. 13

less investigated. Another important criterion in the selection of the index was that it should have at least one sub-criterion where two criteria are met: the best and worst performing countries should not reach the specified extremes; and in this sub-criterion, all countries should have complete data. Only 4 sub-criteria could meet this criterion. In addition, linear scoring functions for the sub-criteria help to present the results in a simple way.

The EPI 2022 ranks 180 countries by 40 performance indicators grouped into 11 issue categories, later into 3 policy objectives: Environmental Health, Ecosystem Vitality, and Climate Change (Wendling et al., 2022). The criteria tree with the local and global weights of all criteria in Fig. 2 focuses on the indicators that are the most relevant for the present research, so the sub-criteria of Climate change and Environmental health are not included. The criterion that we modify, BHI (in previous EPI reports and Excel files also referred to as BHV), is highlighted in red colour.

3.1. Scoring functions

The role of scoring functions is to convert the raw data of the performance indicator into a score, which lies between the minimum and maximum thresholds. In this way, the scores of different performance indicators become comparable, regardless of their measurement unit. The calculation of the normalized score for a given entity and a performance indicator is described in Equation (1).

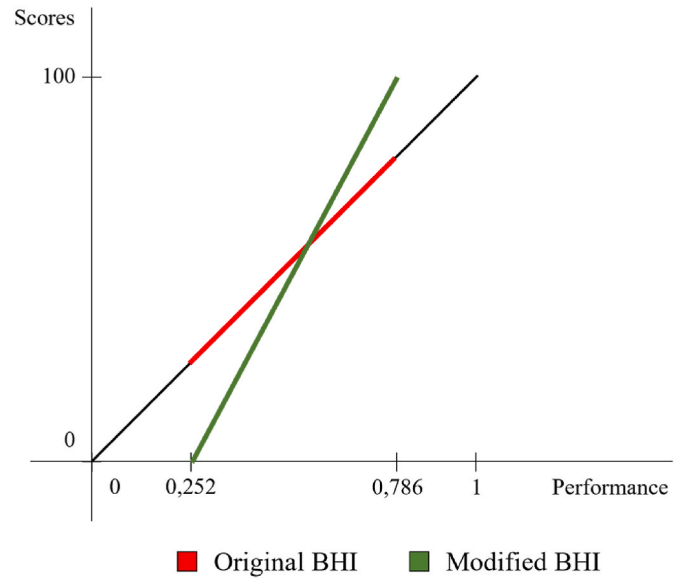

Fig. 4. Modification of the value function of the BHI leaf criterion.

$$Score_{i,p} = \frac{RawData_{i,p} - Threshold_p^{Min}}{Threshold_p^{Max} - Threshold_p^{Min}} \quad (1)$$

where $Score_{i,p}$ is the score of entity i of the performance indicator p, $RawData_{i,p}$ is the raw data of the performance indicator, and $Threshold_p^{Max}$ and $Threshold_p^{Min}$ are the maximum and minimum thresholds, respectively. Changes in the minimum and maximum thresholds of performance indicators can have a significant impact on the final ranking and score. Equation (2) shows how the scoring functions change when we change the minimum threshold to $Threshold_p^{\prime Min}$.

$$Score_{i,p}' = \frac{RawData_{i,p} - Threshold_p^{\prime Min}}{Threshold_p^{Max} - Threshold_p^{\prime Min}} \quad (2)$$

However, this impact can be compensated for by adjusting the weights of the performance indicators accurately. By accurately changing the weights, the final ranking and score can remain consistent even with changes in the minimum and maximum thresholds, as shown in Equation (3).

$$Score_{i,p} \times w_p = Score_{i,p}' \times w_p' \quad (3)$$

where w_p is the original weight of performance indicator p, while w_p' is the recalculated weight that produces the same weighted score. Therefore, it is crucial to carefully consider both the thresholds and weights when designing and evaluating performance indicators.

The EPI transforms the raw data of each performance indicator into a single score for each country on a 0–100 linear scale, where 0 is the worst and 100 is the best performance. The calculation methodology of the scores is discussed in the 2022 EPI report (Wendling et al., 2022). Looking more closely at the methodology of the index, the report shows that the scores for each performance indicator are not necessarily calculated in the same way. In some cases, the maximum or minimum scores are adjusted to the country with the highest or lowest raw data, while in other cases the best score is the 95% or 99% of all data and the worst score is 5% or 1%, resulting in more countries with the same point. Furthermore, it can also be defined by a theoretical value, or a global objective.

EPI has no standardised framework for defining optimal target, leading to varied interpretations of what constitutes the best or worst performance for a country. In most cases, no country reaches either 0 or

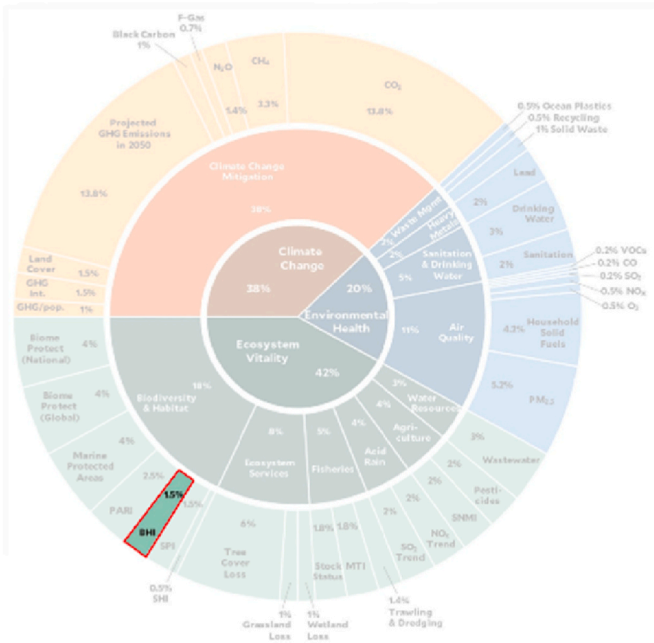

Fig. 5a. BHI leaf criterion in EPI (Wendling et al., 2022).

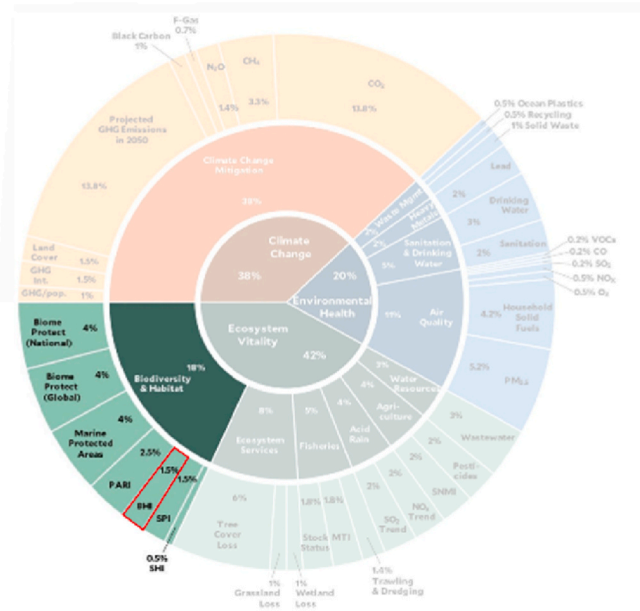

Fig. 6a. Issue Category BDH in EPI (Wendling et al., 2022) highlighted by authors.

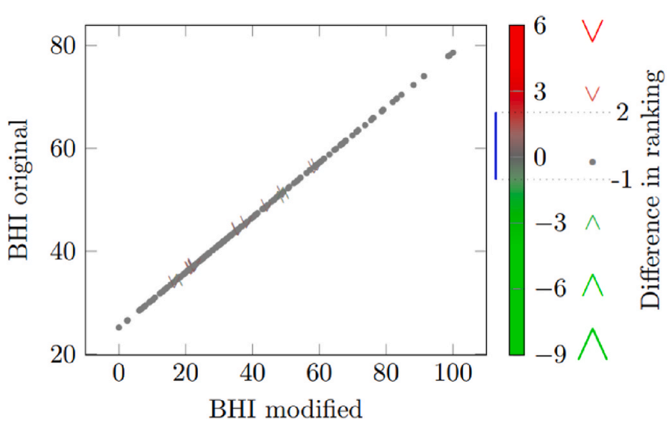

Fig. 5b. Ranking change on the level of the BHI performance indicator due to modifying the value function of the BHI leaf criterion.

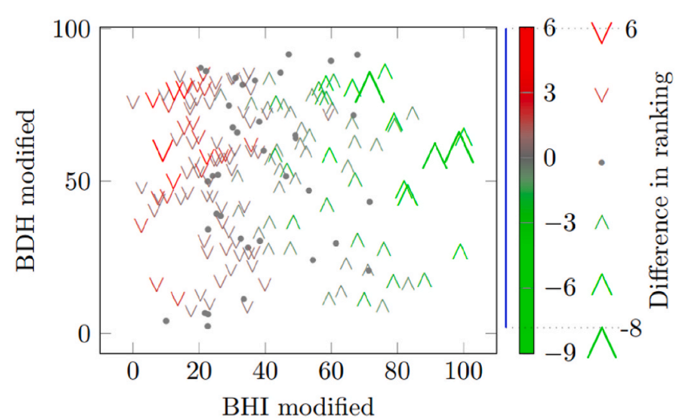

Fig. 6b. Ranking change on the level of the Biodiversity & Habitat (BDH) issue category due to modifying the value function of the BHI leaf criterion.

100 scores, although there are instances where multiple countries reach one or both extremes of the scoring function. For instance, in the assessment of the Wetland Loss indicator, 45 countries attained the maximum score, while in the examination of the Solid Waste indicator, 14 countries scored 0, and 6 countries earned 100. It could be questioned whether there is a single system to follow, but the reasoning behind the chosen methodology must be clearly explained. Various calculation methods may yield differing results, therefore, selecting the appropriate method is crucial. The findings of the authors' research led to the conclusion of even a minor change can affect the final results. Consequently, changing the min/max limits can be an implicit weighting: criteria with smaller min/max ranges are overweighted.

The implicit weighting mechanism, described in Equation (3), is illustrated in Fig. 3. This is a theoretical example where carbon dioxide emissions (smaller the better) are scored on a scale from 0 to 100. In the left figure, the actor with the lowest emission (3 tons) is given 100 points. Rectangles' areas represent the weighted score differences of two actors. 8-3 = 5 tons difference in CO2 emmision results in 0.25*100 = 25 points difference. Whereas in the right figure, zero emission is set to 100 points, thus significantly reducing the score of the actor with the lowest emission. The change will also affect the range of scores, with all actors having lower scores. This change can be compensated for by increasing the weighting of the points to restore the original score. The first score difference can be achieved with larger weight, 0.4*62.5 = 25 (right).

This observation and the main results of our study are not restricted to EPI (Section 4) or DESI (Section 5), they can be extended for any other CIs, see Table 1 in Section 5.

3.2. Data preparation

To emphasize the influence of the scoring function on rankings, we made adjustments in calculating the final EPI scores. The modifications primarily focus on altering the criteria at the leaf level to affect the EPI scores. The score ranges of the leaves are shown in Figure A.1 in Appendix B, which illustrates the variability of the scores, particularly the differences between the maximum and minimum scores. To conduct the experiment, the Biodiversity Habitat Index (BHI) was chosen, as it is the most suitable subject for several reasons. First, the most significant impact resulting from minimal adjustments occurred when modifying the scoring function concerning the BHI performance indicator. It is due to the distance between the thresholds and the extremes, as the

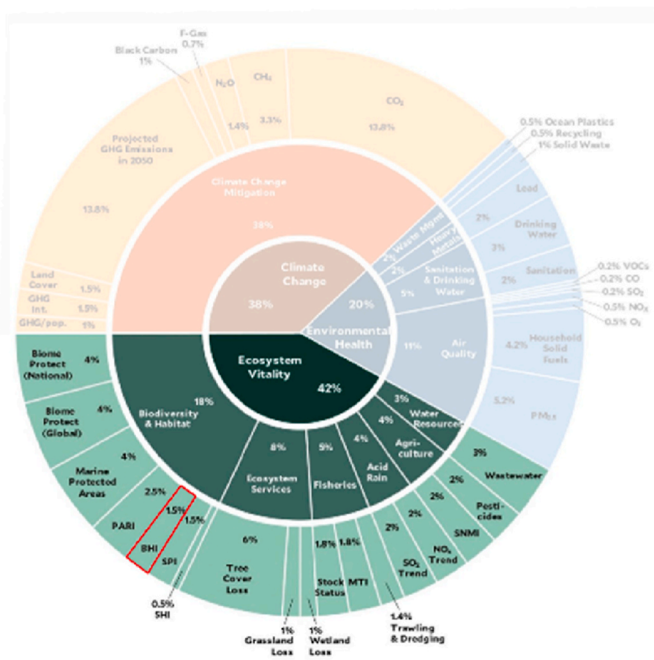

Fig. 7a. Policy objective ECO in EPI (Wendling et al., 2022) highlighted by authors.

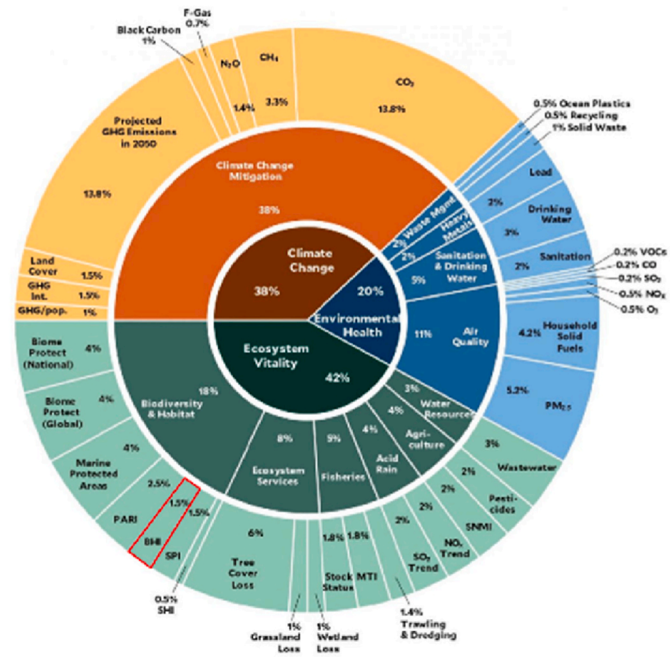

Fig. 8a. EPI (Wendling et al., 2022).

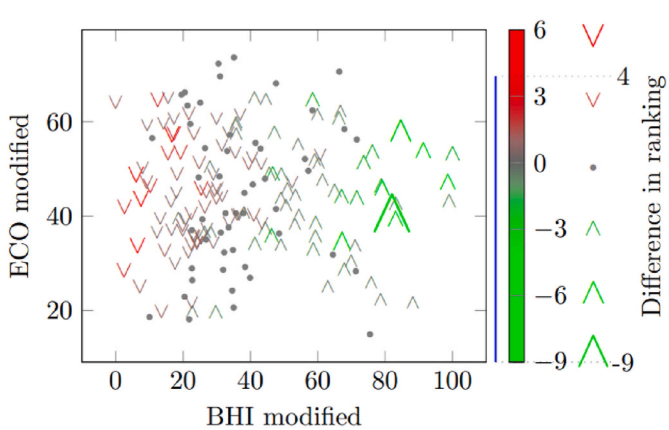

Fig. 7b. Ranking change on the level of the Ecosystem Vitality (ECO) policy objective due to modifying the value function of the BHI leaf criterion.

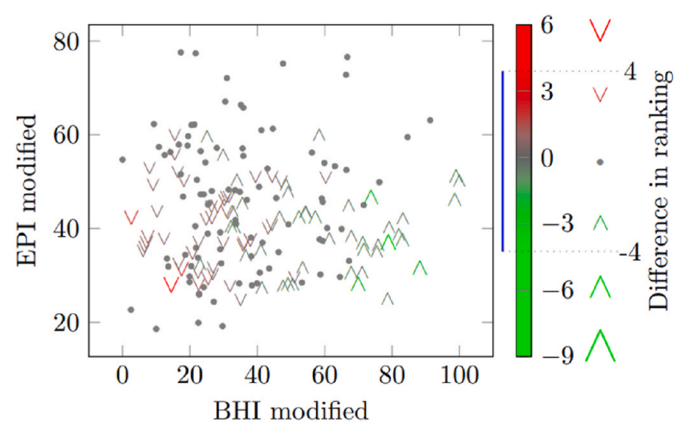

Fig. 8b. Ranking change on the level of the Environmental Performance Index (EPI) due to modifying the value function of the BHI leaf criterion.

minimum and maximum thresholds defined by the original evaluation were far from the worst and best-performing countries. Therefore, the modification of this indicator can generate a more significant impact on the ranking. Second, the availability of comprehensive data across all countries enabled us to accurately replicate the assessment. For other leaf criteria, either substantial data gaps existed or altering them had minimal impact on the rankings. Some criteria displayed more prevalent 0 or 100 scores, creating a non-linear scoring function, which would have hindered the calculation. Additionally, modifying certain leaf criteria would necessitate setting the minimum value to 0, potentially resulting in a division by zero issue. However, despite the circumstantial selection, BHI was suitable to carry out our calculations.

4. Results

The paper aims to contribute to the analysis of scoring functions through a novel approach, which focuses on the min/max thresholds of the functions, while keeps every input data and criteria weight untouched and deviates from the known simulation-based methodologies.

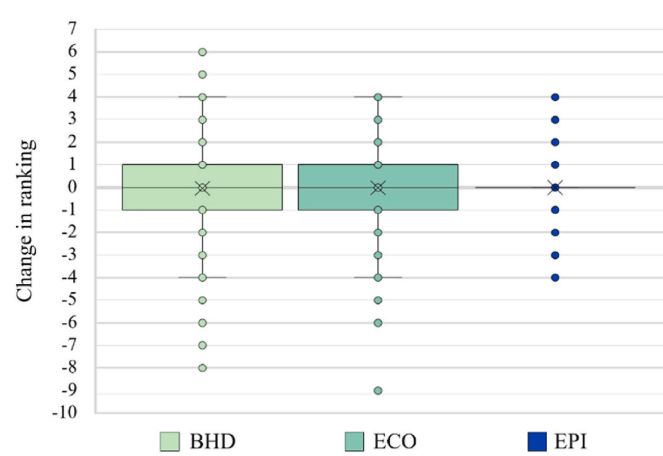

Fig. 9. Changes in the 180 countries' ranking on the different levels of the criteria tree due to the modification of the value function of the BHI leaf criterion.

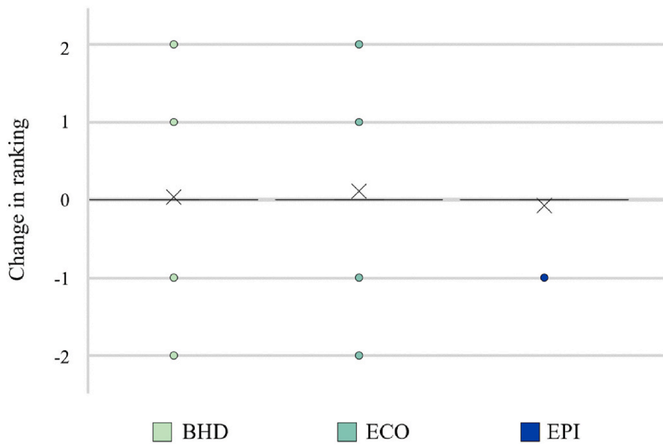

Fig. 10. Changes in the EU 27 countries' ranking on the different levels of the criteria tree due to the modification of the value function of the BHI leaf criterion.

This approach can be interpreted as a form of sensitivity analysis, as it not only impacts the results concerning individual sub-criteria but also influences the overall ranking.

Unlike other sensitivity analyses adding random noise to the input data, our model does not assume any uncertainty. Instead of that, the transformation of criterion-wise performance's raw data (i.e. scoring) is considered. In this view, our approach is a sensitivity analysis with respect to normalization. Minimal and maximal thresholds aim to express the reference points during the scoring process. It is demonstrated that the choice of min/max thresholds is functionally equivalent to a reweighting of the criteria.

4.1. Range of scoring functions

The examination of BHI involved transitioning from using theoretical maximum and minimum values to utilizing actual data from the best and worst-performing countries for scoring BHI. This shift allows us to analyse how the rankings of the 180 countries change across different EPI levels. Referring back to Fig. 2 the BHI falls under the Biodiversity & Habitat issue category (BHD), which is part of the Ecosystem Vitality (ECO) policy objective. The BHI operates on a percentage scale, with the scoring function originally bounded by 0 and 1. However, the raw data from the best and worst-performing countries is between 0.252 and 0.786. As a consequence, none of the countries received scores of 0 or 100. Fig. 4, denoting the positions of all 180 countries based on the original EPI scoring highlighted in red, reveals that these scores utilize only slightly more than half of the 0–100 scale, resulting in narrower intervals between country scores. This methodology overweights the criteria (like BHI) with smaller min/max ranges.

The adjusted scores, showcased in Fig. 4 with green colour, demonstrate an expanded score range due to the modifications. This adjustment created a wider gap between the scores of two similarly performing countries. While this adjustment does not alter the ranking within the BHI, the authors anticipate a potential visible impact when replacing the original data with the modified scores at higher EPI levels.

Having observed how the modified evaluation functions affect scoring within the BHI index, in the next subsection the original BHI scores are replaced with the adjusted ones at higher EPI levels. This aims to scrutinize the broader impact of these minor modifications on the entire index.

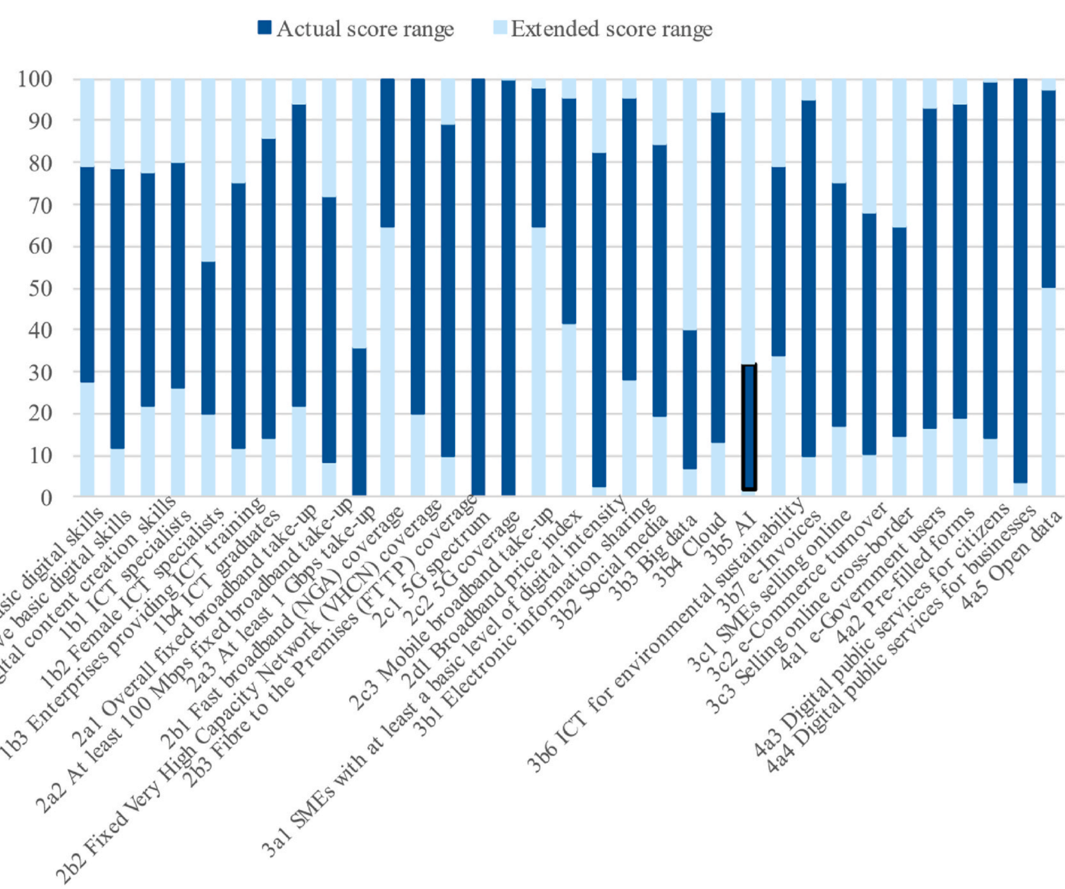

Fig. 11. Actual and 0–100 score range of DESI leaf nodes, see also in worksheet 'Score ranges' in the supplemented DESI Ranking Calculations Excel file.

4.2. Ranking modifier effect

This chapter examines the main results of the analysis of the criteria tree after using the modified BHI values instead of the original values in the overall index. The minor change has significant effects on the different levels of the criteria tree, leading to altered outcomes and conclusions.

The first level of modification is visualised in Fig. 5a. In Fig. 5b, one can see the original BHI values on the vertical axis and the modified BHI points on the horizontal axis. It is clear that a linear transformation of the points has been carried out, however, as the colours and markers suggest, the rankings of some countries are changed at this level. This is because both the original values and the modified ones are rounded to 1 decimal place, thus we break some ties and create some new ones with our transformation. The blue line on the right part of the sub-figure highlights the largest changes in ranking that occurred at this level.

Fig. 6 demonstrates the previous level of the criteria tree. The modified BHI values are still presented on the horizontal axis, in addition, the points of its parent criterion, BDH, appear on the vertical axis (after the modification of BHI). One can see that there is no strong correlation between the two variables (the scatter plot seems to be random enough). On the other hand, the countries that managed to gain the most places in the rankings (denoted by green ∧ signs) are the ones with higher BHI scores, and the ones that lost places the most (denoted by red ∨ signs) are those, that have small BHI points. The largest gain in the rankings of BDH due to the change of BHI is 8 places, while the largest fallback contains 6 places as shown by the blue line as well. These changes are well represented in all parts of the ranking that can be seen from the BDH values (vertical axis).

Fig. 7 represents the level of ECO that is a main criterion. The largest gain of a country in the rankings at this level is 9, while the biggest loss includes 4 places. A strong correlation can be observed between the larger BHI values and the gains in the ranking, which are mainly on the right part of the horizontal axis, while the fallbacks can be observed on the left end. The changes in the rankings are somewhat surprising, but still well-represented in all parts of the order.

Finally, Fig. 8 shows the root of the criteria tree, the level of EPI. Even at this level, some countries gain 4 places or fall back 4 places in the rankings due to our small modification of BHI. The changes are strongly correlated with the BHI values here as well; however, these are more concentrated in the middle and the lower parts of the ranking.

The boxplots in Figs. 7 and 8 depict changes in the ranking of each level of the EPI criteria tree resulting from various approaches. Fig. 9 provides an overview of all 180 countries examined by the Yale EPI, while Fig. 10 focuses on the examination of the EU 27 countries.

The vertical axis of the plots shows the direction and extent of ranking shifts for each country, relative to the original EPI ranking. The X represents the average of the data, typically zero, indicating the number of countries moving forward versus backward. However, Fig. 10 exhibits a non-zero average due to modifications made to break ties in the original ranking. These modifications are noticeable in the overall ranking of the Index, as well as in the ranking of the EU member countries. The latter is significant because EU countries tend to compare themselves to other similarly performing EU countries, and small changes can have a significant impact on such comparisons.

By going through the calculation using the EPI example (the steps of the proposed methodology for the EPI example are detailed in the second column of Table C.1), we would like to highlight the importance and ranking changing effect of scoring functions. A change in the scoring function of a performance indicator is significant even at the very top levels of the index. Changing the scoring function has as significant effect on the ranking as changing the weight, therefore the modification of the min/max frontiers can be used as an implicit weighting.

As it was mentioned earlier, countries follow the rankings, and try improving their rank. But environment related decisions and policies go not only for extra EPI scores, but, more importantly, have real

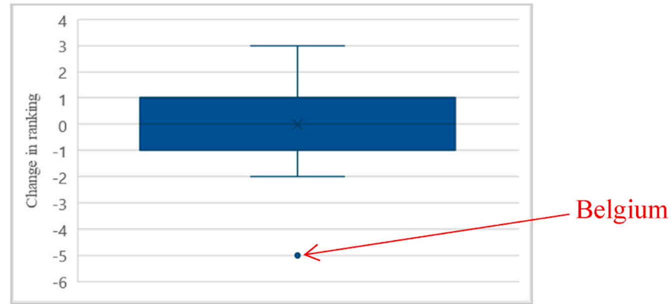

Fig. 12. Changes in the ranking of the DESI modifying the thresholds of the scoring functions with Excel Solver to maximise the sum of absolute changes in the ranking.

consequences and overall effects on the environment, society and economy. Although every composite index is arbitrary for some extent, the most important ones are widely accepted and developed or refined year by year. Still, the direct maximization of, e.g., the EPI score may not be optimal in reality. In particular if some methodological twists have already been identified, it cannot be optimal.

5. Digital Economy and Society Index (DESI)

While in the previous section we exemplified the importance of the scoring functions through the EPI in detail, the same changes can be applied to any other CI that relies on minimum and maximum thresholds within the scoring functions. In this section we demonstrate the impact of adjusting the maximum threshold on the ranking of the Digital Economy and Society Index (DESI).

The DESI is a composite indicator published by the European Commission. It measures the digital performance of EU countries based on four main dimensions: (1) Human capital; (2) Connectivity; (3) Integration of digital technology; and (4) Digital public services (EC, 2022a,b,c). The DESI provides a comprehensive overview of how digital technologies are shaping economies and societies across Europe. It serves as a valuable tool for policymakers, businesses, and researchers to assess digital progress and identify areas for improvement.

The indicator is based on 33 indicators that are normalized and aggregated into sub-dimensions and dimensions. The normalization is done using minimum and maximum thresholds, which are fixed across the different versions of the DESI to allow comparisons over time. This has been done carefully, taking into account the Digital Decade objectives and historical trends, in order to anticipate the evolution of the indicators and to minimize anomalies (EC, 2022a,b,c).

However, this means that for some indicators there is a significant gap between the observed values and the maximum threshold of the scoring function. This is particularly the case for the indicators measuring the leading digital transformation trends, such as artificial intelligence (AI) and big data. The AI indicator is measured by the percentage of enterprises using any AI technology. In the 2022 DESI dataset, the maximum score achieved in the area of AI is 32 (as shown in Fig. 11), as the maximum threshold is set at 75% and the highest observed value is 24% in Denmark.

Lowering the maximum threshold of the AI indicator from 75% to 39%, which is still well away from the maximum observed value and leaves room for future increases in the indicator, has a considerable impact on the final DESI ranking. The adjustment to the maximum threshold changes the order of the ranking in three places. It even modifies the first two places in the ranking, with Denmark taking the lead from Finland. There is also a swap between the 12th and 13th place (France and Germany), and between the 22nd and 23rd place (Hungary and Slovakia).

Furthermore, the impact of modifying the minimum and maximum thresholds for all indicators on the ranking is investigated. Initially, the minimum and maximum thresholds were set to the lowest and highest observed values, respectively. This approach guarantees that the scores attained by the countries will range between 0 and 100 in the case of all indicators. Consequently, the weight imposed by the score ranges is equal for all indicators within this extended range. The application of the minimum and maximum thresholds results in 11 alterations to the ranking. For instance, Croatia progresses from the 20th position to the 18th. The extended thresholds are shown in Fig. 11.

Nevertheless, it is feasible to devise alternative configurations of thresholds that facilitate more substantial shifts in the ranking. To this end, we employed the Evolutionary method of Excel Solver to devise alternative threshold combinations that assess the resilience of the ranking. The Evolutionary method, which employs a genetic algorithmic approach, aims to identify optimal or near-optimal solutions by generating a population of solutions. This population is subjected to random mutation and natural selection (Powell and Batt, 2011). The algorithm was set up to maximise the sum of absolute changes in the ranking. This approach enables the generation of a ranking exhibiting significantly larger changes. Using the thresholds calculated by the evolutionary method, Belgium's ranking drops from 16th to 21st place, a decline of five places relative to the initial ranking. Conversely, Cyprus, France, and Italy experience an improvement of three places. The ranking modification effect of this model is illustrated in Fig. 12.

The calculations presented illustrate the importance of developing sensitivity tests for the thresholds of scoring functions, in conjunction with sensitivity tests of indicator weights. The two calculations present two distinct approaches to sensitivity analysis. The first approach offers a general methodology for comparing the ranking against an alternative where the importance of the indicators are equalised. This is achieved by extending the score ranges to 0–100 for all indicators. The second approach is more complex, employing an advanced method to explore the largest absolute changes in the ranking. Both methods are suitable for testing the robustness of the results of any indices, which eliminates the uncertainty arising from adjusting the thresholds of the scoring functions. Detailed calculations can be tracked in the supplemented DESI Excel file, while the steps of the proposed methodology in the case of the DESI composite indicator are detailed in the third column of Table C.1.

6. Outlook to other indicators

A remarkable portion of composite indices apply min/max thresholds in the scoring procedure. To demonstrate our assumption, we have collected some of these indices for which the implicit weighting effect of changing the scoring function could also be applied. The list of indicators with min-max range transformation is collected in Table 1.

The high number of CIs indicates the significance of evaluating the sensitivity of the rankings to alterations in the min/max thresholds utilized in the scoring methodology.

7. Conclusion and future research

This study focuses on composite indicators, some of which play an important role in real governmental and strategic decisions, on allocating resources. Every single step of the CI's calculation becomes significant from the final result's point of view. By investigating the effect of changing the minimal and maximal Digital Economy and Society Index thresholds of the scoring functions, the authors examine a special sensitivity analysis that is barely studied in the literature. The general observation is exemplified by the Environmental Performance Index (EPI) that even such a minor modification can cause remarkable changes in the ranking. This is important when, for example, countries receive support based on their ranking on an indicator where even a small change in the ranking can push a country into a different category (similar to e.g., the Scimago Q1-Q4 categorization of scientific journals), thereby falling from or gaining financial support.

The adjustment of the minimum and maximum thresholds of performance indicators can be seen as an implicit weighting mechanism. This is because it affects the relative importance of different metrics in determining overall performance. Contrary to former studies, this paper quantifies the effect of this implicit weighting, which is a key contribution. The simultaneous treatment of more (or all) criteria was further tested in the research. The result partially supported the premise that the more the thresholds of several criteria change, the more the ranking changes. They may cancel each other out. However, it can be argued that changing the scoring functions has a large impact on the ranking results.

It is important to emphasize that the phenomenon works the same way in the case of other composite indices (including the ones in Table 1) as well. Therefore, our research suggests the extension of the sensitivity analysis of the indices to the scoring functions, by investigating the impact of uniformly setting the thresholds of the scoring functions on the ranking. This can be applied by setting the thresholds to the minimum and maximum values of each criterion. Alternatively, maximising the sum of absolute changes in the ranking with the optimal modification of the thresholds. In addition, particular emphasis should be placed on those performance indicators in each index where the range of scores is significantly smaller than for the other performance indicators, as these results are given a different implicit weight in the ranking. Each step of the proposed methodology and its realization in the case of the two examined composite indicators (EPI and DESI) are presented in Table C.1.

Uncertainty-based sensitivity approaches and the min/max threshold analysis can also be used together, possibly leading to a more comprehensive understanding of the ranking and its robustness.

Decision makers, creators and users of composite indices would certainly benefit from getting feedback on whether their original intention (expressed by weights of criteria) remain unbiased through the evaluation (scoring) process.

CRediT authorship contribution statement

Adél Kelemen: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Data curation. **Zsuzsanna Katalin Szabó:** Writing – review & editing, Writing – original draft, Supervision, Methodology. **Sándor Bozóki:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Zsombor Szádoczki:** Writing – review & editing, Writing – original draft, Supervision, Methodology. **Áron Dénes Hartvig:** Writing – review & editing, Visualization, Software, Methodology, Investigation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

The paper develops a study of Adél Kelemen (Kelemen, 2021) that has been presented at the Scientific Students' Associations of Corvinus University of Budapest in 2021. The research has been supported in part by the TKP2021-NKTA-01 and FK 145838 NRDIO grants. One of the authors was supported by the ÚNKP-22-3-II New National Excellence Program of the Ministry for Culture and Innovation from the source of the National Research, Development and Innovation Fund.

Appendix D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.indic.2024.100453.

Appendix A

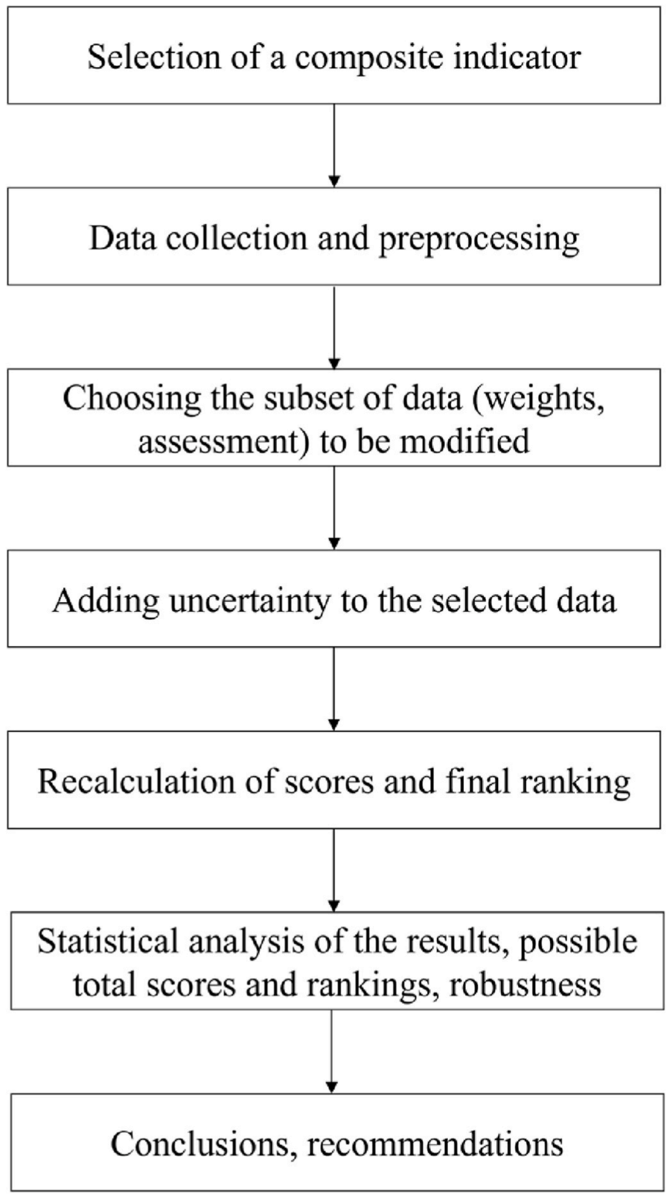

Fig. A.1. The steps of a general sensitivity analysis.

Appendix B

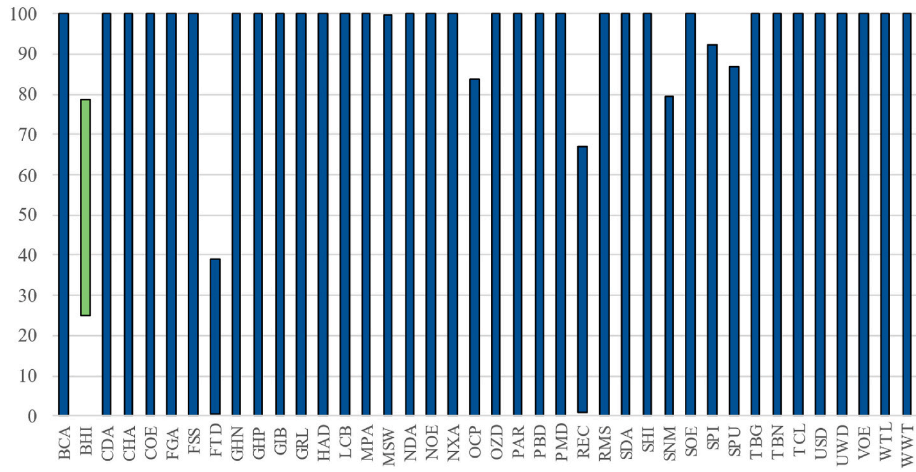

Fig. B.1. Score range of EPI leaf nodes, see also in worksheet 'Score ranges' in the supplemented EPI Ranking Calculations Excel file.

Appendix C

Table C.1
The steps of the proposed methodology and their realization for the EPI and DESI composite indicators.

	EPI (Sections 3 and 4)	DESI (Section 5)
Selection of a composite indicator	The beginning of Section 3	The beginning of Section 5
Data collection and preprocessing	Supplemented EPI Excel file	Supplemented DESI Excel file
Choosing the set of subcriteria to be analyzed	Subsection 3.2	Fig. 11
Modification of min/max thresholds	Supplemented EPI Excel file based on Fig. 4	Supplemented DESI Excel file
Recalculation of scores and final rankings	Supplemented EPI Excel file based on Equations (1) and (2)	Supplemented DESI Excel file based on Equations (1) and (2)
Analysis of the results, comparison to the original ranking, robustness	Subsection 4.2	Fig. 12
Conclusions, recommendations	Closing remarks of Section 4	Closing remarks of Section 5

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