

# A Time-Aware TOPSIS Method for Longitudinal Performance Assessment

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**Abstract.** Multi-criteria decision analysis (MCDA) is widely used to construct composite indicators and rank alternatives across complex domains, yet most applications remain static and evaluate performance using data from a single time period. This limitation can lead to incomplete assessments when alternatives exhibit long-term performance dynamics. This paper proposes a temporal extension of the TOPSIS method that integrates multiple time periods directly into a unified decision framework. The approach expands the decision matrix by introducing temporal instances of each criterion and incorporates time-period weights to model recency effects while preserving the computational simplicity and geometric interpretation of classical TOPSIS. The method is validated through an empirical study based on Environmental Performance Index data for European Union countries using results from 2020, 2022, and 2024. The findings demonstrate that incorporating temporal information produces meaningful ranking differences and enables flexible balancing between historical performance and recent outcomes. The proposed approach provides a transparent and efficient tool for dynamic multi-criteria evaluation.

**Keywords:** temporal MCDA · TOPSIS · composite indicators.

## 1 Introduction

Multi-criteria decision analysis (MCDA) has become a key tool for evaluating complex socio-economic and environmental systems that cannot be captured by a single metric [1,12]. Composite indicators are widely used to compare countries and regions across multidimensional domains such as sustainability and environmental policy [4], transforming heterogeneous data into interpretable rankings that support evidence-based decision-making [8].

Among MCDA techniques, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [7] is one of the most widely adopted methods due to its intuitive geometric interpretation, computational efficiency, and ability to aggregate diverse criteria into a single preference score. Despite its maturity, ongoing research continues to extend the method to improve its robustness and applicability [10,16].

However, most MCDA applications remain static and neglect the temporal evolution of performance. In practice, decision makers rarely assess systems at a single point in time, and relying on cross-sectional data or separate yearly rankings may discard valuable information about long-term trends [16]. The increasing availability of longitudinal datasets highlights the need for MCDA approaches that explicitly incorporate time. Yet only limited research addresses this challenge, leaving a clear gap between dynamic real-world problems and the predominantly static tools used to analyze them [2,6].

This paper aims to bridge this gap by proposing a temporal extension of the TOPSIS method that integrates multiple time periods into a single evaluation framework. Instead of generating independent rankings for each period and comparing them *ex post*, the proposed approach expands the decision matrix to include temporal instances of each criterion and introduces time-period weights that allow flexible modeling of recency effects. The resulting method preserves the simplicity and interpretability of classical TOPSIS while enabling the construction of a unified ranking that reflects the entire performance history of the evaluated alternatives.

The main contributions of this paper are threefold. First, we introduce a simple yet general temporal expansion of the TOPSIS framework that maintains its original computational structure. Second, we demonstrate how different temporal weighting schemes can be used to balance long-term performance and recency emphasis. Third, we validate the proposed approach through an empirical study based on Environmental Performance Index data for European Union countries, illustrating its practical relevance and analytical value.

The remainder of the paper is organized as follows. Section 2 reviews related work on MCDA, TOPSIS, and temporal evaluation approaches. Section 3 presents the proposed temporal TOPSIS extension. Section 4 provides the empirical study and discusses the results. Finally, Section 5 concludes the paper and outlines directions for future research.

## 2 Literature Review

Multi-criteria decision analysis (MCDA) has become a standard methodological framework for constructing composite indicators and benchmarking the performance of countries, regions, and cities across complex and multidimensional domains [14]. Sustainability [13], environmental policy [8], smart city development [18], and socio-economic performance are among the most prominent application areas, where numerous heterogeneous indicators must be aggregated into a single, interpretable ranking [9]. In such contexts, MCDA provides a trans-

parent and flexible framework for integrating diverse criteria and supporting evidence-based policy analysis.

At the same time, the choice of MCDA method can significantly influence the final ranking, even when the same dataset and weights are used [17]. This observation underscores the importance of continued methodological development and careful method selection in composite indicator research.

Among the many MCDA techniques, TOPSIS [7] has emerged as one of the most widely used approaches. Its popularity stems from its conceptual simplicity, intuitive geometric interpretation, and relatively low computational complexity. The method evaluates alternatives by simultaneously considering their distances from a positive ideal solution and a negative ideal solution, producing an easily interpretable preference score.

TOPSIS has been successfully applied across numerous fields, including energy systems [3], environmental management, supply chains [5], healthcare [15], and urban planning [11]. Recent studies confirm the method's adaptability to new problem domains and highlight ongoing efforts to extend the classical formulation of TOPSIS in order to address its various limitations [10,16].

Although many real-world decision problems involve longitudinal data, most MCDA applications remain inherently static. Traditional approaches typically evaluate alternatives using data from a single time period or generate separate rankings for different years and compare them *ex post*. Only a limited number of studies explicitly address the temporal dimension within MCDA [16,6]. This constitutes a clear research gap, which is addressed in this paper by proposing a temporal extension of the TOPSIS method that simultaneously incorporates the temporal dimension of decision-making while preserving the computational simplicity and intuitive geometric interpretation of the original approach.

### 3 Methodology

In this section, the methodological foundations of the proposed approach are presented. First, the classical TOPSIS technique algorithm is presented, followed by the proposed temporal TOPSIS extension algorithm.

#### 3.1 Classical TOPSIS

**Step 1.** Construct the decision matrix. Let  $A = A_1, \dots, A_m$  be a set of alternatives and  $C = C_1, \dots, C_n$  a set of criteria. The decision matrix is defined as Eq. (1):

$$X = [x_{ij}]_{m \times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

**Step 2.** Normalization of the decision matrix. In the standard TOPSIS procedure, min-max normalization is applied to remove differences in scale and

measurement units across criteria. The normalized values  $r_{ij}$  are obtained using Eq. (2) for benefit-type criteria and Eq. (3) for cost-type criteria.

$$r_{ij} = \frac{x_{ij} - \min_j(x_{ij})}{\max_j(x_{ij}) - \min_j(x_{ij})} \quad (2)$$

$$r_{ij} = \frac{\max_j(x_{ij}) - x_{ij}}{\max_j(x_{ij}) - \min_j(x_{ij})} \quad (3)$$

**Step 3.** Weighted normalized matrix. Next, the weighted normalized decision matrix is computed, according to Eq. (4).

$$v_{ij} = w_j r_{ij} \quad (4)$$

**Step 4.** Determination of ideal and anti-ideal solutions. Positive ideal solution (PIS) and the negative ideal solution (NIS) are derived using Eq. (5) Eq. (6), respectively.

$$v_j^+ = \{v_1^+, v_2^+, \dots, v_n^+\} = \{\max_j(v_{ij})\} \quad (5)$$

$$v_j^- = \{v_1^-, v_2^-, \dots, v_n^-\} = \{\min_j(v_{ij})\} \quad (6)$$

The PIS consists of the maximum values of the weighted normalized matrix, whereas the NIS contains the minimum values. Because normalization has already been performed, no further distinction between benefit and cost criteria is required at this stage.

**Step 5.** Distance to ideal solutions. For each alternative, the distances to the PIS and NIS are calculated using Eq. (7) and Eq. (8). The Euclidean metric is used as the standard distance measure in the TOPSIS method.

$$D_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2} \quad (7)$$

$$D_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \quad (8)$$

**Step 6.** Calculation of the preference score. Finally, the performance score of each alternative is computed using Eq. (9).

$$C_i = \frac{D_i^-}{D_i^- + D_i^+} \quad (9)$$

The resulting  $C_i$  value lies in the interval  $[0, 1]$ , and the alternative with the highest score is considered the most preferable. Consequently, the final ranking is obtained by sorting alternatives in descending order of their preference scores.

### 3.2 Temporal TOPSIS Extension

Assume performance datasets are available for a range of  $T$  consecutive time periods  $t_0, t_1, \dots, t_{T-1}$ , where  $t_0$  denotes the most up-to-date period,  $t_1$  a previous period and consequently  $t_{T-1}$  the oldest period. In our novel proposed approach, we extend the classical TOPSIS to accommodate all studied periods into a single decision matrix, as described in the following procedure.

**Step T1.** Temporal expansion of the decision matrix. For each criterion  $C_j$ , we define its temporal instances:

$$C_j^{(t_k)}, \quad k = 0, \dots, T-1 \quad (10)$$

The temporal decision matrix becomes:

$$\hat{X} = [x_{i,j,k}]_{m \times (n \cdot T)} \quad (11)$$

where  $x_{i,j,k}$  denotes the performance of alternative  $A_i$  under criterion  $C_j$  in period  $t_k$ .

Thus, the number of criteria increases from  $n$  to  $nT$ .

**Step T2.** Temporal weights. Let  $w_j$  be the original weight of criterion  $C_j$  and let  $\lambda_k$  denote the weight of time period  $t_k$  such that

$$\sum_{k=0}^{T-1} \lambda_k = 1, \quad \lambda_k \geq 0 \quad (12)$$

Each temporalized criterion receives the weight:

$$w_{j,k}^{\hat{}} = w_j \lambda_k \quad (13)$$

It follows that the new weights remain normalized:

$$\sum_{j=1}^n \sum_{k=0}^{T-1} w_{j,k}^{\hat{}} = 1 \quad (14)$$

This formulation allows emphasizing recent periods by assigning larger  $\lambda_k$  values.

**Step T3.** Temporal impacts. The type of each criterion (benefit or cost) is assumed time-invariant. Therefore, the impact of  $C_j^{(t_k)}$  equals the impact of  $C_j$ :

$$\text{impact}_{j,k}^{\hat{}} = \text{impact}_j \quad (15)$$

**Step T4.** Classical TOPSIS application. After the temporal expansion, the TOPSIS procedure is applied without further modification, using the extended decision matrix  $\hat{X}$ , weights  $w_{j,k}^{\hat{}}$  and impacts  $\text{impact}_{j,k}^{\hat{}}$ .

The proposed approach integrates temporal dynamics directly into the decision space. Instead of aggregating rankings across time, the proposed approach preserves period-specific information, allows flexible temporal importance modeling, and produces a single ranking reflecting the entire performance history.

Table 1: EPI issue categories used as 11 criteria in the empirical study.

Policy Objective	Abbreviation	Weight	Issue Category
ECO - Ecosystem Vitality	BDH	0.18	Biodiversity & Habitat
	ECS	0.08	Ecosystem Services
	FSH	0.05	Fisheries
	APO	0.04	Air Pollution
	AGR	0.04	Agriculture
	WRS	0.03	Water Resources
HLT - Environmental Health	AIR	0.11	Air Quality
	H2O	0.05	Sanitation & Drinking Water
	HMT	0.02	Heavy Metals
	WMG	0.02	Waste Management
PCC - Climate Change	CCH	0.38	Climate Change

## 4 Empirical Study

In this section, a practical demonstration of the proposed approach is presented, on a case study on the temporal assessment of Environmental Performance Index (EPI). The Environmental Performance Index is a widely recognized composite indicator that evaluates how effectively countries protect environmental health and maintain ecosystem vitality. Developed by researchers from Yale University and Columbia University, the EPI aggregates dozens of indicators into thematic categories such as climate change mitigation, air quality, biodiversity, water resources, and sustainable agriculture. By transforming diverse environmental metrics into a standardized ranking, the index enables cross-country comparison and helps policymakers, researchers, and stakeholders monitor progress, identify strengths and weaknesses, and track changes in environmental performance over time.

The EPI is published on a biennial basis. For the purposes of this case study, data from the 2024, 2022, and 2020 editions were collected, as these reports rely on a highly consistent set of issue categories, which makes them suitable for the application of the proposed temporal TOPSIS extension. The analysis incorporates all 11 EPI issue categories, which are summarized in Table 1 together with the relative importance weights assigned to them within the EPI framework.

In this study, the analysis covers all 27 European Union countries, using data extracted from the 2024, 2022, and 2020 EPI reports. Following the methodology proposed in this paper, the three performance matrices were integrated into a single temporal TOPSIS decision matrix, illustrated in Fig. 1. For each issue category, countries receive scores ranging from 0 to 100, where higher values indicate better environmental performance; lower values are highlighted in red and higher values in blue. In several instances, data was unavailable for certain countries and categories, which fact was denoted in the EPI reports as either NA or -9999. In this study, the -9999 notation is retained, as it could be directly incorporated into the computational procedure.

Air.	C10	C11	C12	C20	C21	C22	C30	C31	C32	C40	C41	C42	C50	C51	C52	C60	C61	C62	C70	C71	C72	C80	C81	C82	C90	C91	C92	C100	C101	C102	C110	C111	C112	
A1R	74.3	86	85.5	47.5	28	35.6	9999	9999	9999	92.9	100	100	72.5	70.6	68	87.3	94	94	61.5	75	81.3	96	94.7	94.7	92.3	90.7	91.7	63.8	77.4	97.2	54.1	50.3	71.3	
AUT	66.2	82.4	87.4	43.6	16.3	32.5	8	16.4	9	98.3	100	100	68.5	33.1	47.3	81.7	68.2	67.9	64.8	74.6	80.7	93.3	93.6	93.6	85.2	66.6	67.4	65.1	68	97.6	59.7	48.1	70.2	
BGR	69.2	75.1	77.1	37.4	41.4	21.9	23.8	12.9	32.3	100	100	100	74.2	55.8	63.6	66.3	33.8	33.8	33.8	33.8	33.8	33.8	33.8	33.8	33.8	33.8	33.8	33.8	33.8	33.8	33.8	33.8	33.8	
HRV	69.6	81.5	82.6	61.7	34.4	40.3	62.1	26	11.8	91.1	100	100	90.8	67.9	68.9	65.4	74.1	69	51.7	40.5	45.8	50.8	84.8	70.3	70.2	72	74.2	75.1	39.1	55.3	80	56	56.6	70
CYP	51.2	78.3	56.5	60.6	32.5	38.6	43.6	6.2	20.2	83.3	92.5	91.5	35.7	13.9	27.7	70.2	50	50	55.9	68.3	73.1	89.4	94	93.9	70.9	68.6	69.4	31.7	58.9	77.5	42.6	53.8	63.1	
CZE	78.9	83.3	85.7	22.5	19.1	26.7	9999	9999	9999	93.8	100	100	74	37.4	58.7	79.1	61.5	60.8	50.4	53.3	58.8	79.3	76.5	76.4	84.8	75.5	76.4	51.2	74.9	89.5	52.2	52.8	76.3	
DNK	53.1	76.9	81.7	51	16.4	30.2	44.7	10.9	13.2	90.3	100	100	77.8	75.7	78	83.3	100	100	100	70.9	80.5	85.5	93.6	97.5	97.4	100	100	100	65.5	68.3	99.8	67.1	92.4	98
EST	78.8	86	87	28.9	15.2	22.4	70.4	40.8	16.4	91.5	100	100	96.6	71	61.8	51.8	69.6	70.4	69.6	60.9	74.6	80.3	80	61.9	61.9	72.6	86.5	87.4	65.1	66.7	74.4	82.8	52	59
FIN	59.1	71.1	75.5	60.8	20.1	20.8	90.4	42.4	12.8	92.8	100	100	93.1	66.6	62.7	52.4	82.5	100	100	82.2	93.5	98.8	100	100	100	100	100	100	68.4	69.6	97.7	71.8	83.6	77
FRA	61.5	86.5	88.3	58.6	21.5	36.1	43.2	19.5	12.1	92.8	100	100	72.8	49.5	65.2	82.5	88	88	65.2	82	88.1	88.2	96.3	96.2	98.9	83.1	84	59.6	63.8	94.8	61.3	49.5	81.9	
DEU	80.4	88.5	88.8	38.5	17.9	39.7	36.4	26.9	14	92.6	100	100	90	78.8	60.9	61.9	89.1	97	97	66.9	75.2	81.1	100	99.1	99	98.7	89.8	90.7	67.4	69	97.9	64.9	47.2	71.5
GRC	62.4	69.1	72.6	58.2	28.1	43.9	47.8	15.6	15.7	88	78.7	78.8	61.4	38.9	52.6	83.1	81.7	81.7	53.7	62	67.5	96.6	98.2	98.2	71.1	68.6	69.4	39.4	59.5	81	71.3	50.8	66.6	
HUN	66.9	78	82	50.1	28	28.2	9999	9999	9999	93.3	100	100	96.9	69.2	53	73.1	86.2	55.3	53.8	38.6	38.2	42.8	73.5	62.2	62.2	65.7	67.4	68.2	51.7	43.4	89.2	49.2	48.1	71.3
IRL	62.5	59.6	65.8	9999	17.4	27.4	40.6	18.2	9.1	87.3	95.4	100	72.9	48.7	47.3	72.5	87	89.7	76.8	89.1	94	95.6	97.4	97.4	97.3	81.8	82.7	60.7	67.9	81.7	51.1	48.2	66.6	
ITA	58.5	76.5	75.6	55	26.1	37.9	34	16.8	14.9	89.5	100	100	81.4	56.4	38.8	56.8	72.7	58.8	58.8	52.2	69.4	75.9	98.6	98.3	98.2	83.6	80.6	81.5	57.5	60.6	83.7	53.2	48.2	88.1
LVA	62.4	84.3	86.7	31.8	35.8	21.4	69	38.4	7.3	82.8	95	94.8	64.4	64.4	62.8	68	90.7	90.7	45.1	51.1	58.8	82.4	99.1	99	71.9	77.5	78.4	42.8	63	85.8	52.4	58.6	67.7	
LUX	74.9	84.4	87.5	45.9	21.9	24.6	80.1	13.4	14.5	83.2	95.5	96.6	67	65.6	64.1	72.7	52.3	51.4	53.2	58.4	62.7	75.8	58.4	58.3	75.4	83	83.9	61.3	67.4	87.8	52.4	47.1	65.9	
LTU	84.8	84.8	85.5	46.1	18.1	34.3	9999	9999	9999	84.3	100	100	62.8	55.9	42.2	90.6	98	98.5	67.1	81	87.2	99.8	98.7	98.6	100	95.1	96.1	63.8	79.1	96.2	62.4	67.4	77.5	
MAL	67.1	72.9	75.1	9999	100	100	56.9	47.8	12.2	83.3	100	100	80.8	43.8	28.3	28.3	52.3	0	0	69.8	73.2	77.6	95.3	99.8	99.8	67.4	49.9	50.6	27.1	63.5	56.7	68.6	82.8	62.6
NLD	60.5	80.1	83.7	62	24.4	42.8	22.5	13	13.1	92.6	100	100	68	29.3	40	89.2	100	100	67.4	76.8	82.4	91.1	100	100	100	84.1	95.1	69.8	66.3	80.8	60.7	54.5	55.8	
POL	81.4	87.3	88	48.4	17.7	27.1	57.8	11	8	83.5	99.6	89.6	68.3	42.7	57.4	77.5	61.5	60.9	38.5	40.4	44.7	80.1	71.8	71.7	69.1	64.5	65.3	58.2	63.7	91.1	53.5	38.8	65.4	
PRT	59.8	70.5	73	16.5	8.6	7.4	31.1	14.7	33.1	88.7	100	100	93.5	49.7	23.5	22.3	85.8	59.2	55	61.1	78.1	84.4	96.4	83.5	83.4	75.4	64.6	65.3	50.8	62.5	90.2	55.3	37.6	63.3
ROU	71.9	81.1	85	57.1	35	40.9	24.5	66.3	54.5	86.8	95.9	100	67.8	53.8	65.7	51.4	25.7	30.4	39.3	39.2	43.6	68	56	55.9	57.1	50.8	51.4	42.3	45.6	65.8	49.3	51.3	84.6	
SRB	88.8	82.7	85	53.5	19.9	32.1	9999	9999	9999	84.1	100	100	67.4	68	68.8	58.3	44.7	43.7	50.5	50.9	56.2	92.6	71.9	71.8	70.9	68.4	69.2	53.4	62.2	80.6	48.9	53.5	71.9	
SVN	64.9	84.5	86.4	58.9	34.1	37.1	86.4	9999	9999	92.7	100	100	90	56.7	55	47	70.7	82.2	89.1	45.8	55.1	60.9	91.2	74.7	74.7	96.6	87.8	88.1	53.6	66.7	83.8	57.5	62.9	75.2
ESP	66.9	85.8	87.8	44.5	13.4	24.4	33.7	16.4	17.9	89.3	100	100	54.1	31.8	36.2	78.7	91.1	91.5	56.2	74	80.2	93.8	96.9	96.8	81.7	70.5	71.3	50.8	61.4	89	57.2	41.3	71.2	
SWE	60	68.8	72.5	56.2	29.3	22.4	52.4	15.3	11.6	90.6	100	100	73.2	74	63.6	84.5	100	100	100	81.1	94	98.2	96.9	98.6	98.5	100	96.9	98	72.7	70.8	99.8	62.9	75.4	77.2

Fig. 1: Color-coded visual representation of the temporal decision matrix.

To benchmark the proposed approach, the final EPI scores for all considered periods were first collected. Subsequently, for each period, the classical TOPSIS method was applied to rank the countries. All criteria were treated as benefit-type attributes, since the maximum score of 100 represents the best achievable performance for each indicator. Moreover, the original EPI weights were adopted for all criteria (see Table 1). The resulting rankings are reported in Table 2.

Eventually, the proposed temporal TOPSIS extension was applied to evaluate the countries under the EPI criteria. The same impacts and weights were retained; however, instead of producing three separate rankings for individual time periods, the objective was to obtain a single ranking that jointly reflects performance across all analyzed periods.

Three alternative period-weighting schemes were considered. First, all periods were assigned equal importance ( $\lambda = [1, 1, 1]$ ). Second, greater emphasis was placed on more recent periods by assigning progressively higher importance to each subsequent period ( $\lambda = [3, 2, 1]$ ). Finally, a stronger recency effect was examined by weighting each subsequent period as twice as important as the previous one ( $\lambda = [4, 2, 1]$ ). The resulting rankings are also reported in Table 2.

We begin with the scenario in which all three periods are treated as equally important. The classical TOPSIS evaluation for the most recent period ( $t_0$ , i.e., 2024) identifies Estonia as the top-performing country, followed by Finland, Germany, Greece, and Luxembourg. The official EPI ranking likewise places Estonia first in 2024, although some differences appear in subsequent positions.

When the temporal dimension is incorporated and the years 2022 and 2020 are given the same importance as 2024, the ranking changes noticeably. Estonia falls to the 6th place, while Denmark becomes the leader, followed by Finland and Luxembourg. The differences between the 2024 classical TOPSIS ranking and the temporal TOPSIS results with equal period weights are illustrated in Fig. 2a. Countries located on the diagonal line retain identical positions in both rankings; this occurs for only a small subset, including Finland (2nd), Malta (8th), Croatia (16th), and Cyprus (27th). Most countries exhibit at least minor shifts, such as Slovakia (19th in 2024 versus 18th temporally), while others

Table 2: Comparison of rankings produced by the proposed temporal TOPSIS extension with varying  $\lambda$  period weights, classic TOPSIS for 2024, 2022, 2020, and original EPI evaluation ranks for 2024, 2022 and 2020.

Country	Symbol	Temporal TOPSIS			TOPSIS			EPI		
		$\lambda = [1, 1, 1]$	$\lambda = [3, 2, 1]$	$\lambda = [4, 2, 1]$	2024	2022	2020	2024	2022	2020
Austria	AUT	13	13	13	14	12	11	6	7	4
Belgium	BEL	11	12	11	10	17	12	12	16	10
Bulgaria	BGR	24	26	26	26	23	21	26	25	27
Croatia	HRV	16	14	15	16	8	15	20	13	23
Cyprus	CYP	27	27	27	27	14	27	27	17	20
Czechia	CZE	12	15	16	17	16	7	14	15	13
Denmark	DNK	1	3	3	6	1	1	7	1	1
Estonia	EST	6	2	1	1	10	22	1	11	19
Finland	FIN	2	1	2	2	3	5	4	2	5
France	FRA	5	9	9	9	11	2	9	9	3
Germany	DEU	7	7	5	3	13	9	3	10	7
Greece	GRC	15	8	6	4	24	24	8	21	16
Hungary	HUN	23	25	25	25	25	14	24	24	22
Ireland	IRL	25	24	24	23	26	23	13	19	11
Italy	ITA	22	22	23	22	21	20	22	18	13
Latvia	LVA	19	19	20	21	7	16	23	12	25
Lithuania	LTU	20	20	19	18	18	18	17	23	24
Luxembourg	LUX	3	4	4	5	5	4	2	5	2
Malta	MLT	8	6	8	8	2	25	10	3	15
Netherlands	NLD	14	10	10	11	9	17	10	8	8
Poland	POL	21	17	17	13	22	19	16	26	26
Portugal	PRT	26	23	22	20	27	26	21	27	18
Romania	ROU	10	21	21	24	19	3	25	22	21
Slovakia	SVK	18	18	18	19	15	13	15	14	17
Slovenia	SVN	9	11	12	15	6	8	19	6	12
Spain	ESP	17	16	14	12	20	10	18	20	9
Sweden	SWE	4	5	7	7	4	6	5	4	6

experience substantial changes, for example Romania (24th in 2024 versus 10th temporally).

These differences stem from the inclusion of historical performance. Denmark, ranked 6th in 2024, rises to 1st place in the temporal ranking due to its leading positions in both 2022 and 2020. A similar pattern explains Romania's improvement in the temporal approach: despite a low position in 2024, it performed considerably better in earlier editions, which substantially strengthens its overall temporal standing. However, one may argue that results from four years earlier should not influence the current assessment to such a degree. For this reason, the next stage of the analysis introduces a damping approach, in which earlier periods receive progressively lower weights than more recent ones.

In the second variant, a recency-oriented weighting scheme was introduced in which the years 2020, 2022, and 2024 were assigned weights of 1, 2, and 3, respectively (subsequently normalized prior to their application). Under this setting, Denmark no longer occupies the leading position and falls to 3rd place (see Table 2). Finland becomes the top-ranked country, reflecting consistently strong results across all three periods (2nd in 2024, 3rd in 2022, and 5th in 2020), while Estonia moves to 2nd place (1st in 2024, 10th in 2022, and 22nd in 2020). The remaining ranking shifts are illustrated in Fig. 2b.

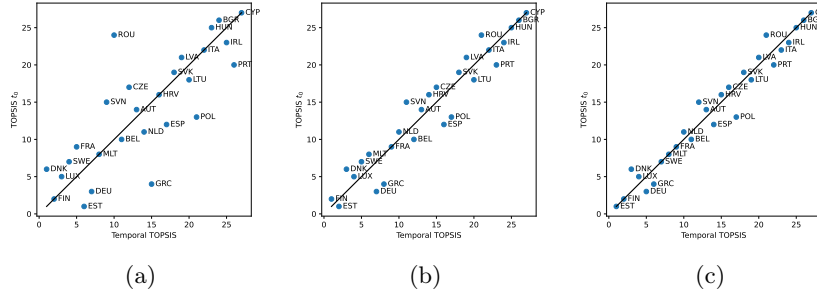


Fig. 2: Visual comparison of the TOPSIS rankings in period  $t_0$  on the y-axis and the proposed temporal approach with period weights a)  $[1, 1, 1]$ ; b)  $[3, 2, 1]$ ; c)  $[4, 2, 1]$  on the x-axis.

In the final scenario, an even stronger recency effect was imposed by assigning weights of 1, 2, and 4 to the years 2020, 2022, and 2024, respectively (again normalized before use). The corresponding results are reported in Table 2, and the differences relative to classical TOPSIS for 2024 are shown in Fig. 2c. Under this scheme, Estonia regains the leading position, with Finland moving to second place. This outcome reflects the dominant influence of the most recent period: the substantially higher weight assigned to 2024 amplifies the impact of current indicator values, while the contribution of the earliest period becomes comparatively minor. A similar pattern is observed for Denmark, which ranked 6th in 2024 but 1st in the two earlier periods. Despite its strong historical performance, Finland’s superior results in 2024 allow it to remain ahead of Denmark, which ultimately secures 3rd place rather than the 6th position implied by the most recent data alone.

The empirical study concludes with an analysis of the correlations among all rankings considered in this work. The resulting correlation matrix is shown in Fig. 3. The first three entries correspond to the rankings obtained using the proposed temporal TOPSIS extension, with  $\lambda$  representing equal period weights, moderate recency emphasis, and strong recency emphasis. These are followed by the original EPI rankings for 2024, 2022, and 2020, and finally by the classical TOPSIS rankings computed separately for each of these years.

Several clear clusters can be identified. A strong correlation is observed among the original EPI rankings across the three editions, which is expected since the same 11 criteria are applied to all 27 countries in each biennial assessment. Although national environmental performance evolves over time, such changes are typically gradual, leading to substantial similarity between consecutive rankings.

A comparable pattern emerges for the classical TOPSIS rankings based on the EPI criteria and weights. In this case, the 2024 results show stronger correlation with 2022 than with 2020, further highlighting the persistence and slow evolution of performance across EPI indicators.

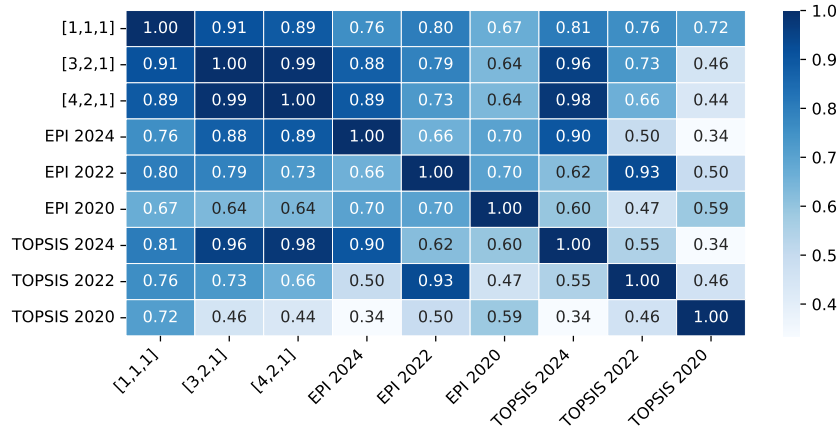


Fig. 3: Correlation matrix between various ranking creation approaches.

When the temporal TOPSIS results are compared with the single-year classical TOPSIS rankings, a clear trend appears: the greater the weight assigned to the most recent period (2024), the stronger the correlation with the 2024 classical ranking. The correlation coefficient increases from 0.81 for equal weights  $[1, 1, 1]$ , to 0.96 for moderate recency emphasis  $[3, 2, 1]$ , and reaches 0.98 for strong recency emphasis  $[4, 2, 1]$ . Nevertheless, the coefficient never reaches unity, confirming that the incorporation of temporal information produces meaningful differences, as also illustrated by the ranking comparisons in Fig. 2.

Overall, the empirical results confirm that incorporating temporal information into the evaluation provides a more comprehensive and nuanced assessment of countries' environmental performance. The proposed temporal TOPSIS extension not only produces rankings consistent with single-period analyses but also reveals meaningful shifts driven by historical performance and alternative recency weighting schemes, thereby demonstrating its practical applicability and added analytical value in long-lasting decision-making contexts.

## 5 Conclusions

This paper introduced a temporal extension of the TOPSIS method designed to support multi-criteria decision-making problems in which performance evolves over time. Instead of aggregating or comparing rankings obtained independently for different periods, the proposed approach integrates the temporal dimension directly into the decision matrix by expanding the criterion space and introducing time-period weights. This formulation preserves the structure and computational simplicity of classical TOPSIS while enabling a unified ranking that reflects the entire performance history of the evaluated alternatives.

The empirical study based on EPI data for the European Union countries demonstrated the practical relevance and analytical value of the proposed approach. The results confirmed that incorporating historical information leads to meaningful changes in rankings, especially when countries exhibit different long-term trajectories. The temporal TOPSIS rankings consistently remained strongly correlated with single-period rankings, yet never identical to them, indicating that the method provides additional insights rather than merely reproducing existing results. Moreover, the experiments showed that the choice of time-weighting scheme plays a crucial role in shaping the final ranking, allowing decision makers to control the balance between long-term performance and recency effects. This flexibility is particularly valuable in policy-oriented evaluations, where both historical consistency and current performance may be important.

Overall, the obtained results confirm that the proposed temporal TOPSIS extension constitutes a simple, transparent, and computationally efficient tool for dynamic multi-criteria evaluation problems. By preserving temporal information and enabling adjustable recency emphasis, the method offers a meaningful alternative to traditional single-period assessments and to approaches that aggregate rankings across time.

Several promising research directions emerge from this study. First, the proposed temporal expansion concept could be extended to other multi-criteria decision-making methods, including distance-based approaches such as VIKOR and SPOTIS, as well as outranking methods from the European school, such as PROMETHEE, which offers additional analytical capabilities through GAIA-based visualization and clustering of criteria. Second, further research could investigate alternative temporal weighting schemes, including data-driven or adaptive approaches. Finally, a systematic comparison with existing temporal evaluation frameworks, particularly DARIA-TOPSIS, would provide valuable insights into the advantages and limitations of different strategies for incorporating time into multi-criteria decision analysis.

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