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A Multi-Criteria Framework for Economic Decision Support in Urban Sustainability: Comparative Insights from European Cities

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ABSTRACT

Sustainable urban development has become an economic imperative as cities grapple with escalating environmental, social, and financial pressures. This study evaluates the economic performance and fiscal sustainability of European capitals—Stockholm, Oslo, Copenhagen, Lahti, London, Berlin, Madrid, Paris, Amsterdam, and İstanbul—through a robust Multi-Criteria Decision-Making (MCDM) framework. The analysis incorporates twelve key indicators that reflect not only environmental resilience but also resource efficiency, infrastructure investment, and the economic viability of sustainability policies. These include Scope 1 Emissions, Consumption-Based GHG Emissions, Particulate Air Pollution, Open Public Space, Road Infrastructure Efficiency, Sustainable Transport, Vehicle Dependence, Water Access, Water Consumption, Solid Waste Generated, Climate Change Resilience, and Sustainable Policy Implementation. A hybrid MCDM model combining MEREC-based RAWEC with Extended AROMAN and MARA methods was applied. The MEREC method was used to derive economically weighted priorities among criteria, while final rankings were aggregated using RAWEC, Extended AROMAN, MARA, and Borda Count methods. Results identified Scope 1 emissions as the most economically impactful criterion, while particulate air pollution had a lower fiscal weighting. Cities such as Stockholm, Oslo, and Copenhagen consistently emerged as top performers due to their cost-effective and forward-looking urban sustainability policies. In contrast, Paris, İstanbul, and Amsterdam demonstrated lower cost-efficiency scores. Sensitivity analysis further validated the model's reliability. This framework not only supports environmental assessment but also informs economic decision-making by guiding policymakers toward fiscally responsible and sustainable urban planning strategies.

1. Introduction

In recent decades, sustainable cities have garnered significant attention and are increasingly recognized worldwide as an effective strategy for tackling urban sustainability challenges. According to United Nations projections, by 2050, 66% of the global population is expected to reside in urban

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areas. This trend poses substantial challenges to both environmental and social sustainability. Additionally, the design of sustainable cities has been identified as a contributing factor to various ecological and social issues. Currently, cities are responsible for approximately 70% of global resource consumption, making them major energy consumers and key sources of greenhouse gas (GHG) emissions. This is primarily due to the high density of urban populations, the intensity of their economic and social activities, and inefficiencies within the built environment [1]. The focus on sustainable development in academic and political spheres has shifted from a primary emphasis on environmental issues to a broader consideration of environmental, social, and economic factors. This shift has led to the emergence of sustainable cities, which proactively respond to challenges such as environmental degradation and the necessity for resilient urban environments. Recognizing this, the United Nations has identified establishing sustainable cities and communities as a key objective within its Sustainable Development Goals [2]. Multiple nations worldwide are embracing sustainability initiatives, as evidenced by the emergence of new sustainable cities. This trend in urban planning underscores a renewed emphasis on developing human capital, promoting healthy living environments, and embracing environmental stewardship. To be classified as sustainable, a city must incorporate several key components, including sustainable education, the utilization of renewable energy, energy efficiency, sustainable transportation, environmentally friendly buildings, and effective waste management [3].

Urban Europe is characterized by its high population density, robust job markets, and dynamic economic activities, and currently stands at a pivotal moment. The region is grappling with a threefold crisis: ongoing public health challenges resulting from the COVID-19 pandemic, a socio-economic crisis that has exacerbated existing inequalities, and urgent climate and ecological issues. Addressing these interconnected challenges necessitates that cities and their residents become key drivers and active participants in fostering sustainable transitions towards an inclusive, environmentally sound, and socially equitable future. Many European cities are making significant strides towards sustainability by implementing impactful reforms and embracing the Sustainable Development Goals. For instance, cities like London, Stockholm, Milan, and Oslo, along with notable cities in Norway such as Bergen, Stavanger, and Trondheim, have enacted legislation for congestion pricing that includes exemptions for electric vehicles, aimed at reducing air pollution and encouraging environmentally responsible travel among motorists [4]. Accordingly, cities across Europe are increasingly focused on becoming more innovative and sustainable, underscoring the necessity for effective assessment frameworks to evaluate these initiatives. The European Union is committed to transforming urban environments into innovative and sustainable spaces, as reflected in its strategic investments in various innovative city projects [5]. Additionally, the EU aims to address the challenges related to urbanization while promoting sustainable growth in its urban areas [6]. Following this, a range of indicator-based approaches has been developed to assess various dimensions of urban sustainability. Additionally, several ranking indices have emerged to measure the sustainability levels of cities, particularly for benchmarking urban areas in Europe. Among the most notable of these indices are the Sustainable Cities Index [7], European Smart Cities ranking [8], the Green City Index [9], the European Green Capital Award [10], and the European Green City Index [11].

MCDM has emerged as a well-established methodology in the literature for assessing performance across various fields [12-15]. However, a singular ranking method cannot effectively represent each country's complex structure of sustainability. MCDM facilitates the incorporation of diverse perspectives and criteria, resulting in aggregate measures that offer a more nuanced understanding of progress across various dimensions of sustainability. This approach is especially crucial when assessing complex Sustainable Development Goals, such as Sustainable Cities and

Communities. Considering the numerous factors involved—pollution, waste management, transportation, land use, and social well-being—a comprehensive evaluation is essential for formulating effective urban development policies [16]. The current paper employs a hybrid MEREC-based RAWEC, Extended AROMAN, MARA, and Borda Count decision model to assess the performance of sustainable cities across ten European capitals. The primary aim of this study is to address the following research questions:

RQ1. What are the key factors influencing the performance of sustainable cities in the selected European countries?

RQ2. How do the European capitals compare in terms of sustainable cities' performance?

RQ3. Are there variations in the performance of sustainable cities among the selected European countries based on the MCDM methods utilized?

The rationale for adopting this hybrid model can be summarized as follows: (i) The MEREC method is notable for its simple, straightforward procedures that avoid complex calculations. This approach utilizes a categorical-based evaluation method, effectively integrating decision-makers' intuitive assessments of different criteria [17]. (ii) The RAWEC method consolidates the evaluation process into a single stage, streamlining the required steps. It emphasizes assessing outcomes by analyzing deviations from ideal values rather than merely ranking options based on their decision matrix values. Its user-friendly methodology showcases substantial potential for application in MCDM, as it minimizes intricate calculations [18]. (iii) The Extended AROMAN method improves upon the original AROMAN approach by incorporating attribute normalization and weight sensitivity, resulting in more accurate and equitable rankings of alternatives [19]. (iv) The MARA method offers a practical and adaptable framework for addressing complex MCDM problems, with strengths including its applicability, flexibility in real-world scenarios, relatively short computation times, and inherent simplicity, all of which are acknowledged in the developed decision algorithm [20]. (v) Lastly, the Borda Count method synthesizes multiple rankings to mitigate the influence or bias of any single method or opinion, thereby enhancing the robustness of the results [21].

The novelties of this study can be summarized as follows:

i. A novel hybrid decision-support framework has been designed to assess the sustainable performance of various European capitals comprehensively. This novel approach incorporates numerous dimensions of sustainability, suggesting a systematic approach to assessment.
ii. To the best of the author's knowledge, this study marks the first instance of concurrently employing the MEREC-based RAWEC, Extended AROMAN, MARA, and Borda Count methods within the MCDM field. Integrating these techniques enhances the methodological diversity and improves the decision-making process within the model.
iii. The proposed hybrid model is a functional tool for policymakers, urban planners, private sector representatives, and other stakeholders seeking to evaluate, compare, and analyze sustainability performance across various urban environments.
iv. The model's robustness and validity have been tested through sensitivity analysis, thus confirming its reliability for reasonable decision-making applications.

The structure of this paper is as follows: Section 2 reviews the existing literature. Section 3 outlines the data and research methodology employed. Section 4 presents the findings derived from the hybrid MCDM methods. Finally, Section 5 concludes with a summary of the results, emphasizing recommendations and implications for future research.

2. Literature Review

The rapid and widespread urbanization of the human population raises important concerns regarding the sustainability of cities [22]. The sustainable development of urban areas is increasingly recognized as essential for achieving collectively established sustainability goals at local, regional, and global levels, and more broadly, for ensuring the well-being of humanity worldwide. The United Nations Sustainable Development Goals (SDGs) include a specific goal related to cities (Goal 11), with many other goals and targets that have urban applications and implications across multiple scales [23]. Due to the' complex characteristics of sustainable cities, various MCDM methods have been widely utilized to assess their performance based on multiple criteria.

Yi *et al.,* [24] examined the sustainability of 13 cities within the Capital Economic Circle in China by utilizing the IOWA operator. Their findings revealed that the sustainable development levels of Beijing and Tianjin were significantly higher than those of the other cities in the study. In a separate analysis, Chen [25] evaluated the sustainable livability of 13 major cities in China using various MCDM methods, including the Gini coefficient, TS fuzzy neural network, TOPSIS, fuzzy Borda, and PCA. The results indicated that Hangzhou emerged as the most livable city, while Beijing ranked as having the least favorable urban environment. Ozkaya and Erdin [26] assessed the smartness and sustainability of 44 cities globally through a hybrid MCDM approach that combined ANP and TOPSIS techniques. Their analysis ranked Tokyo, London, and New York as the top three cities in overall sustainability. Hajduk [27] analyzed smart cities across 66 Polish cities using the TOPSIS method. The results indicate that Kraków, Wrocław, and Jastrzębia Góra have attained an excellent level of urban smartness. Klumbytė *et al.,*[28] employed AHP-based WASPAS and COPRAS methods for sustainable decision-making in 20 municipal buildings in Lithuania. Their findings from the Kaunas City Municipality revealed that 20% of social housing buildings were positioned at the end of the priority queue and were in the worst condition. Adali *et al.,* [29] evaluated the smartness levels of 17 European cities using integrated grey-based methods (LBWA-G and EDAS-G). Their analysis ranked London, Paris, and Amsterdam as the top three cities, while Helsinki, Milan, and Istanbul were at the bottom. [30] assessed the sustainability performance of thirty metropolitan areas in Türkiye using the IT2F-AHP and COPRAS methods. Their findings identified Antalya, Muğla, and Eskişehir as the top performers, whereas Istanbul and Izmir showed comparatively lower performance.

Another recent study by [31] assesses the environmental competitiveness of cities in Iran using an integrated approach that combines the ITARA-FUCOM-based MARCOS-LN methods. Their findings indicate that Rasht is ranked as the most environmentally competitive city, while Kerman is identified as the least competitive among the examined cities. Kutty *et al.,* [32] analyze the sustainability, resilience, and livability of European smart cities using an innovative fuzzy expert-based multi-criteria decision support model. Their results reveal that London is the highest-ranked smart city, closely followed by Düsseldorf, Zurich, and Munich. Furthermore, the Norwegian capital, Oslo, as well as Dublin, Amsterdam, Hamburg, Rome, Moscow, and Stockholm, are categorized within the high-performance cluster. Brodny *et al.,* [33] assess living conditions and quality of life in smart sustainable cities in Poland by applying the EDAS and WASPAS methods. Their analysis demonstrates that the most significant cities, specifically Warsaw, Wrocław, Gdańsk, and Poznań, exhibit the best living conditions and quality of life performance. Lin and Zheng [34] have developed a knowledge-based MCDM approach to evaluating the urban performance of smart cities, with a specific focus on Singapore. The results indicate that Singapore excels in performance, reflecting its integration of advanced technologies and community-oriented strategies.

In summary, a significant body of literature has examined the performance measurement of sustainable cities through MCDM approaches. However, many of these studies are constrained by a limited regional focus, often targeting specific locations. Additionally, they rely on traditional evaluation models and do not adequately incorporate novel methodologies. This research aims to overcome these limitations by proposing a novel and comprehensive MCDM framework that systematically integrates multiple dimensions of sustainability. Unlike previous studies, this research applies the framework to assess the performance of various European capitals, thus providing a more holistic and comparative perspective.

3. Materials and Methodology

3.1. Materials

This paper evaluates the sustainability performance of European capitals, focusing specifically on Stockholm, Oslo, Copenhagen, Lahti, London, Berlin, Madrid, Paris, Amsterdam, and İstanbul, through a hybrid MCDM model. The Corporate Knights Sustainable Cities Index has an annual ranking that assesses the environmental sustainability initiatives of cities worldwide. This index utilizes 12 quantitative metrics, each contributing to a comprehensive score that reflects a city's overall sustainability. These metrics encompass various aspects of urban environmental performance, including greenhouse gas emissions, air quality, transportation, and waste management [7]. The methodology for assessing sustainable city performance has undergone significant evolution, particularly since its initial version in 2011. While the original evaluation relied on five key indicators, a refinement was introduced in 2022 by Corporate Knights, increasing the framework to twelve criteria. These enhancements improved the accuracy, comparability, and reliability of the assessments. The revised methodology currently provides a more comprehensive and standardized evaluation of sustainable cities, making it a more effective tool for policymakers and businesses. As a result, the analysis of sustainable city performance was conducted using twelve criteria: Scope 1 Emissions, Consumption-Based GHG Emissions, Particulate Air Pollution, Open Public Space, Road Infrastructure Efficiency, Sustainable Transport, Vehicle Dependence, Water Access, Water Consumption, Solid Waste Generated, Climate Change Resilience, and Sustainable Policies. The assessment indicators were selected based on a comprehensive review of the existing literature [35-38] and are grounded in a solid conceptual framework that aligns with international standards for evaluating urban sustainability from both economic and environmental perspectives

The data was obtained from the “2023 Sustainable Cities Index” reports published by Corporate Knights (https://www.corporateknights.com/rankings/sustainable-cities-rankings/). The twelve criteria have been systematically categorized into two functional groups:

v. Benefit-Oriented Criteria: This group includes open public spaces, sustainable transportation, access to clean water, resilience to climate change, and the implementation of sustainable policies. These criteria have been chosen for their potential to generate direct societal and economic benefits.

vi. Non-Benefit-Oriented Criteria: This category consists of scope 1 GHG emissions, consumption-based greenhouse gas emissions, particulate air pollution, road infrastructure efficiency, vehicle dependency, water consumption, and solid waste generation. These criteria demonstrate the operational inefficiencies and environmental externalities that urban areas seek to mitigate.

This classification facilitates an economic interpretation of sustainability, emphasizing the optimization of resource allocation (efficiency) while minimizing externalities (costs) concurrently. The data utilized in this analysis were derived from the 2023 Sustainable Cities Index published by Corporate Knights, which provides consistent and methodologically validated information across the European capital cities included in this study. Table 1 provides a summary of the criteria along with their brief descriptions. The decision matrix was also created using data gathered from the reports, as shown in Table 2.

Table 1
Overview of Criteria

Criteria	Abbr.	Opt.	Unit	Description
Scope 1 GHG Emissions	C_1	Cost	Tonnes CO2e/capita	Divide the city's sector-based inventory of Scope 1 emissions by the city's population. This indicator reflects fossil fuel consumption in the city.
Consumption-Based GHG Emissions	C_2	Cost	Tonnes CO2e/capita	Divide the city's consumption-based GHG emissions inventory by the city's population.
Particulate Air Pollution	C_3	Cost	PM 2.5 μg/m3	Micrograms of fine particulates (less than 2.5 μm diameter) per cubic metre of air, a standard indicator of air quality.
Open Public Space	C_4	Benefit	Fraction of city area that is Open Public Space (%)	Divide the city area for public parks, recreation areas, greenways, and other areas accessible to the public by the total city area.
Road Infrastructure Efficiency	C_5	Cost	Road Density (km/km2)	Divide the length of the road network in kilometres by the square kilometres of the city area.
Sustainable Transport	C_6	Benefit	Fraction of trips by walking, cycling and public transit (%)	Divide the number of trips by sustainable modes (walking, cycling, or public transit) by the total of all trips.
Vehicle Dependence	C_7	Cost	Vehicles/ Household	Divide the number of registered road vehicles by the number of households.
Water Access	C_8	Benefit	% of population with access	The percentage of the city population with access to potable water.
Water Consumption	C_9	Cost	Litres/ capita/ day	The average amount of water consumed in litres per capita per day.
Solid Waste Generated	C_{10}	Cost	Tonnes/ year/ capita	Divide the amount of municipal solid waste generated in tonnes per year by the city population.
Climate Change Resilience	C_{11}	Benefit	ND-GAIN Readiness/ Vulnerability	Divide the national Notre Dame GAIN Readiness Score by the Notre Dame GAIN Vulnerability Score.
Sustainable Policies	C_{12}	Benefit	Number of sustainable policies enacted (/5)	Starting with an assessment of the number of key policies tracked by REN21 that the city has enacted: (i) renewable energy target, (ii) electric vehicle target, (iii) emission reduction target, (iv) net-zero GHG target, and (v) renewable energy enabling policy

Source: [7]

Table 2
Decision Matrix

Opt.	max	max	max	max	max	min	min	min	min	min	min	min
Alternative/ Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
Stockholm	47.70	49.00	100.0	2.4416	4	0.4320	7.5203	6.00	1.28	0.0917	180.0	0.2293
Oslo	20.49	68.00	100.0	2.9779	4	1.1686	13.2669	7.50	0.29	0.7064	183.0	0.3452
Copenhagen	24.75	70.00	100.0	2.1934	3	0.7423	9.5662	9.70	0.34	0.8232	104.0	0.4100
Lahti	15.70	45.50	100.0	2.4234	4	3.5223	13.1491	5.90	0.23	0.7499	120.0	0.5024
London	33.00	58.00	100.0	2.3079	5	2.3973	8.3154	9.80	1.72	0.4921	144.0	0.4000
Berlin	8.06	75.00	100.0	2.3539	5	2.6034	10.8435	12.50	1.80	0.6457	120.0	0.3672
Madrid	6.70	64.80	100.0	1.7890	3	1.8719	6.7839	9.40	1.32	0.2382	132.0	0.4058
Paris	3.65	73.00	100.0	2.0935	4	1.3968	7.0611	13.70	1.92	1.0560	149.0	0.4254
Amsterdam	13.00	78.00	100.0	1.9468	1	2.9610	17.5784	10.30	3.29	0.4750	142.5	0.4060
Istanbul	3.07	71.00	99.3	1.3824	2	2.0198	6.4769	26.50	0.47	0.8694	189.0	0.3911

Table 2
Continued

Opt.	max	max	max	max	max	min	min	min	min	min	min	min
Alternative/ Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
max	47.70	78.00	100.0	2.9779	5	3.5223	17.5784	26.50	3.29	1.0560	189.0	0.5024
min	3.07	45.50	99.3	1.3824	1	0.4320	6.4769	5.90	0.23	0.0917	104	0.2293

3.2. Methodology

In this study, a decision support system was developed to assess the sustainability performance of European capitals. The system enables the evaluation and ranking of cities based on established sustainability criteria. The proposed decision support framework utilizes the MEREC-RAWEC-Extended AROMAN-MARA hybrid model, structured into two stages comprising a total of twenty-three steps. In Stage 1, criteria weights are determined using an objective weighting approach. A criteria evaluation matrix is initially constructed based on data from the report, and the first set of criteria weights is established through the MEREC method. In Stage 2, various MCDM methods, including RAWEC, Extended AROMAN, and MARA, are employed to evaluate and rank the cities based on their sustainability performance. During this stage, the final criteria weights are applied, and logarithmic normalization techniques are used to generate the ultimate rankings of the alternatives. The methodological flow of the proposed hybrid approach is presented in Fig. 1.

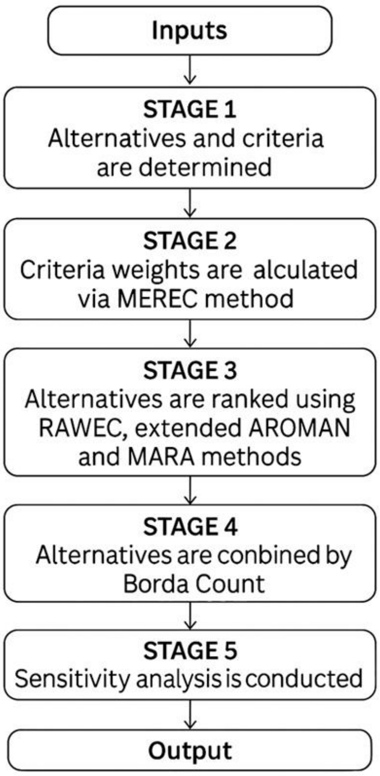

Fig. 1. Diagram of the MEREC-RAWEC-Extended AROMAN-MARA hybrid model

3.2.1. MEREC Method

The Method based on the Removal Effects of Criteria (MEREC) was introduced by Keshavarz-Ghorabaee et al. in 2021 as a novel objective weighting approach for determining the weights of criteria. This method assesses the impact of removing each criterion on the performance of alternatives to derive the weights of the criteria. The MEREC method involves the following steps [17]:

Step 1. The decision matrix is established.

Step 2. The decision matrix is normalized through Eqs. (1-2).

$$N_{ij} = \left\{ \frac{\min_k x_{kj}}{x_{ij}} \right\} if\ j \in B \quad \text{for beneficial/maximum set of criteria} \tag{1}$$

$$N_{ij} = \left\{ \frac{x_{ij}}{\max_k x_{kj}} \right\} if\ j \in B \text{for non-beneficial/minimum set of criteria} \tag{2}$$

Step 3. The overall performance of the alternatives *(S_i)* is determined using the Eq. (3).

$$S_i = \ln\left(1 + \left(\frac{1}{m}\sum_j \left|\ln(N_{ij})\right|\right)\right) \tag{3}$$

Step 4. According to Eq. (4), the performance of the alternatives by removing each criterion is calculated.

$$S'_{ij} = \ln\left(1 + \left(\frac{1}{m}\sum_{k,k\neq j} \left|\ln(N_{ij})\right|\right)\right) \tag{4}$$

Step 5. The summation of absolute deviations is computed via Eq. (5).

$$E_j = \sum_i \left|S'_{ij} - S_i\right| \tag{5}$$

Step 6. The final weights of criteria are determined based on Eq. (6).

$$w_i = \frac{E_i}{\sum_K E_k} \tag{6}$$

3.2.2. RAWEC Method

The Ranking of Alternatives with Weights of Criterion (RAWEC) method was introduced by Puška et al. in 2024. This approach simplifies the decision-making process by reducing the number of required steps and eliminating the need for complex calculations. Puška *et al.,* [18] provide a detailed outline of the steps involved in the RAWEC method.

Step 1. The decision matrix is formed.

Step 2. According to Eqs. (7-8), the decision matrix is normalized using a double normalization approach.

$$n_{ij} = \frac{x_{ij}}{x_j\ max}, and\ n'_{ij} = \frac{x_j\ min}{x_{ij}}, for\ benefit\ criteria, and \tag{7}$$

$$n_{ij} = \frac{x_{j\ min}}{x_{ij}}, and\ n'_{ij} = \frac{x_{ij}}{x_{j\ max}}, for\ cost\ criteria. \tag{8}$$

Step 3. In this phase, deviation from the criterion weights is assessed using Equations (9-10). This method effectively combines the weighting of the normalized decision matrix with an evaluation of the discrepancies from the established criteria weights.

$$v_{ij} = \sum_{i=1}^{n} w_j \,.\, (1 - n_{ij}) \tag{9}$$

$$v'_{ij} = \sum_{i=1}^{n} w_j \,.\, (1 - n'_{ij}) \tag{10}$$

Step 4. The final ranking of the alternatives is determined using Eq. (11).

$$Q_i = \frac{v'_{ij} - v_{ij}}{v'_{ij} + v_{ij}} \tag{11}$$

The RAWEC method yields a value ranging from -1 to 1. The absolute value of this outcome is utilized to determine the superiority of an alternative, with higher values indicating more favorable options. The alternative that achieves the highest value is considered the optimal choice.

3.2.3. An Extended AROMAN Method

In 2023, Bošković et al. introduced an improved Alternative Ranking Order Method Accounting for Two-step Normalization (AROMAN) method. This method combines normalized data through a two-step normalization process and computes an average matrix derived from that data. The steps involved in the extended AROMAN method are outlined as follows [19]:

Step 1. The decision matrix is established.

Step 2. The decision matrix is normalized based on a double normalization process using the following equations:

Step 2.1. Normalization Type I (Linear)

$$t_{ij} = (x_{ij} - \underset{i}{minx_{ij}})/(\underset{i}{maxx_{ij}} - \underset{i}{minx_{ij}}), \quad i=1,2,3,\ldots\ldots m,\ j=1,2,\ldots\ldots n. \tag{12}$$

Step 2.2. Normalization Type II (Vector)

$$t^*_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \quad i=1,2,3,\ldots\ldots m,\ j=1,2,\ldots\ldots n. \tag{13}$$

Step 2.3. Aggregated Averaged Normalization

$$t^{norm}_{ij} = \frac{\beta t_{ij} + (1-\beta) t^*_{ij}}{2}, \quad i=1,2,3,\ldots\ldots m,\ j=1,2,\ldots\ldots n. \tag{14}$$

where…. represents the normalized aggregation average, and β is a weighting coefficient that ranges from 0 to 1. In this case, we considered β to be 0.5.

Step 3. The weighted normalized decision matrix is obtained by applying the following equation:

$$\widehat{t_{ij}} = W_{ij} \,.\, t^{norm}_{ij}, \quad i=1,2,3,\ldots\ldots m,\ j=1,2,\ldots\ldots n. \tag{15}$$

Step 4. Separately summarize the normalized weighted values of the criteria type min ($\boldsymbol{L_i}$) and the normalized weighted values of the max type ($\boldsymbol{A_i}$) as follows:

$$L_i = \sum_{j=1}^{n} \widehat{t_{ij}}^{(min)}, \quad i=1,2,3,\ldots\ldots m,\ j=1,2,\ldots\ldots n. \tag{16}$$

$$A_i = \sum_{j=1}^{n} \widehat{t_{ij}}^{(max)}, \quad i=1,2,3,\ldots\ldots m,\ j=1,2,\ldots\ldots n. \tag{17}$$

Step 5. Raise the obtained sum of $\boldsymbol{L_i}$ and $\boldsymbol{A_i}$ values to the degree of $\boldsymbol{\lambda}$ using the following equations:

$$L_i^{\wedge} = L_i^{\lambda} = \left(\sum_{j=1}^{n} \widehat{t_{ij}}^{(min)}\right)^{\lambda} \quad i=1,2,3,\ldots\ldots m \tag{18}$$

$$A_i^{\wedge} = A_i^{1-\lambda} = \left(\sum_{j=1}^{n} \widehat{t_{ij}}^{(max)}\right)^{1-\lambda} \quad i=1,2,3,\ldots\ldots m \tag{19}$$

where λ represents the coefficient degree of the criterion type, in this study, we considered parameter λ to be 0.5.

Step 6. Determine the final ranking of the alternatives by applying following equation:

$$R_i = e^{\left(\hat{A_i}-\hat{L_i}\right)}, \quad i=1,2,3,\ldots\ldots m \tag{20}$$

3.2.4. MARA Method

The Magnitude of the Area for the Ranking of Alternatives (MARA) method was introduced as a recent MCDM technique that aims to create clear rankings among various alternatives. This method is fundamentally centered on two primary functions: one related to the optimal alternative and the other concerning each specific alternative. A pivotal aspect of this approach is the computation of the area beneath both the optimal alternative and each alternative, which is crucial for evaluating the magnitude of these areas. The area associated with each alternative is determined through the definite integration of a linear function over the interval from 0 to 1. The following steps outline the procedure for employing the MARA method [20]:

Step 1. The decision matrix is normalized through Eqs. (21-22).

$$r_{ij} = \frac{x_{ij}}{\underbrace{max}_{i=1,2,3\ldots,m}\ x_{ij}} \tag{21}$$

$$r_{ij} = \frac{\underbrace{min}_{i==1,2,3\ldots,m}\quad x_{ij}}{x_{ij}} \tag{22}$$

Step 2. According to Eq. (23), the weighted normalized decision matrix is created.

$$g_{ij} = w_j r_{ij,} \forall i \in [1,2,3 \ldots\ldots, m], \qquad \forall j \in [1,2,3 \ldots\ldots, n] \tag{23}$$

Step 3. The optimal alternative is determined by utilizing Eqs. (24-25).

$$S_j = \max\left(g_{ij} | 1 < j \leq n\right) \forall i \in [1,2,3 \ldots\ldots, m] \tag{24}$$

$$S = \left\{s_1, s_2, \ldots\ldots\ldots, s_j\right\} \quad j = 1,2,\ldots\ldots, n \tag{25}$$

Step 4. Decomposition of the optimal alternative is established using Eqs. (26-27).

$$S = S^{max} \cup S^{min} \tag{26}$$

$$S = \{s_1, s_2, \ldots\ldots\ldots, s_k\} \cup \{s_1, s_2, \ldots\ldots\ldots, s_l\}\,; k + 1 = j \tag{27}$$

Step 5. The decomposition of each alternative is defined by Eqs. (28-29).

$$T_i = T_i^{max} \cup T_i^{min}, \forall i \in [1,2,3 \ldots\ldots, m] \tag{28}$$

$$T_i = \{t_{i1}, t_{i2}, \ldots\ldots\ldots, t_{ik}\} \cup \{t_{i1}, t_{i2}, \ldots\ldots\ldots, t_{il}\}, \qquad \forall i \in [1,2,3 \ldots\ldots, m] \tag{29}$$

Step 6. For the optimal alternative, the intensity of the element is computed based on Eqs. (30-33).

$$S_k = s_1 + s_2 + \cdots + s_k \tag{30}$$

$$S_l = s_1 + s_2 + \cdots + s_l \tag{31}$$

$$T_{ik} = t_{i1} + t_{i2}, \ldots\ldots + t_{ik}\ \forall i \in [1,2,3 \ldots\ldots, m] \tag{32}$$

$$T_{il} = t_{i1} + t_{i2}, \ldots\ldots + t_{ik}\ \forall i \in [1,2,3 \ldots\ldots, m] \tag{33}$$

Step 7. According to Eqs. (34-38), final ranking of the alternatives is determined.

$$f^{opt}(S_k, S_l) = \frac{S_l - S_k}{1-0}\,(x - S_k) + S_k = (S_l - S_k)x + S_k \tag{34}$$

$$f^{i}(T_{ik}, T_{il}) = \frac{T_{il} - T_{ik}}{1-0}\,(x - T_{ik}) + T_{ik} = (T_{il} - t_{ik})x + T_{ik} \tag{35}$$

$$F^{opt} = \int_0^1 f^{opt}(S_k, S_l)dx = \int_0^1 \big((S_l - S_k)x + S_k\big)dx = \frac{S_l - S_k}{2} + S_k \tag{36}$$

$$F^{i} = \int_0^1 f^{i}(T_{ik}, T_{il})dx = \int_0^1 \big((T_{il} - T_{ik})x + T_{ik}\big)dx = \frac{T_{il} - T_{ik}}{2} + T_{ik};\ \forall i \in [1,2,3 \ldots\ldots, m] \tag{37}$$

$$M_i = \int_0^1 f^{opt}(S_k, S_l)dx - \int_0^1 f^i(T_{ik}, T_{il})dx;\ \forall i \in\ [1,2,3 \dots \dots, m] \quad (38)$$

The final ranking of the alternatives is determined according to the ascending order of M_i

3.2.5. Borda Count Method

The Borda Count method ranks alternatives based on preferences, starting from the most preferred to the least preferred. The alternative that ranks the lowest receives 0 points, with the next lowest receiving 1 point. This pattern continues incrementally, culminating in the highest-ranked alternative receiving points equal to the total number of alternatives. The points assigned to each alternative are then aggregated across all rankings, and the alternative with the highest total Borda count is deemed the best option [39].

4. Results

4.1. The results obtained from the MEREC method

The criteria were initially normalized based on their benefits and cost optimization using Equations (1-2). The resulting normalized decision matrix is presented in Table 3. Following this, the overall performance of the alternatives (S_i) was calculated using Equation (3). Next, the overall performance after removing each criterion (S_{ij}) was determined using Equation (4), as shown in Table 4. The impact of removing each criterion on the overall performance of the alternatives was evaluated through Equations (5-6), which calculated the standard deviation and weight of each criterion, respectively. The results obtained from the MEREC method are summarized in Table 5.

Table 3
Normalized Decision Matrix

Alternative/ Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
Stockholm	0.0644	0.9286	0.9930	0.5662	0.2500	0.1227	0.4278	0.2264	0.3891	0.0868	0.9524	0.4564
Oslo	0.1498	0.6691	0.9930	0.4642	0.2500	0.3318	0.7547	0.2830	0.0881	0.6689	0.9683	0.6872
Copenhagen	0.1240	0.6500	0.9930	0.6302	0.3333	0.2108	0.5442	0.3660	0.1033	0.7795	0.5503	0.8162
Lahti	0.1955	1.0000	0.9930	0.5704	0.2500	1.0000	0.7480	0.2226	0.0699	0.7102	0.6349	1.0000
London	0.0930	0.7845	0.9930	0.5990	0.2000	0.6806	0.4730	0.3698	0.5228	0.4660	0.7619	0.7963
Berlin	0.3809	0.6067	0.9930	0.5873	0.2000	0.7391	0.6169	0.4717	0.5471	0.6114	0.6349	0.7310
Madrid	0.4582	0.7022	0.9930	0.7727	0.3333	0.5315	0.3859	0.3547	0.4012	0.2256	0.6984	0.8079
Paris	0.8411	0.6233	0.9930	0.6603	0.2500	0.3966	0.4017	0.5170	0.5836	1.0000	0.7884	0.8469
Amsterdam	0.2362	0.5833	0.9930	0.7101	1.0000	0.8407	1.0000	0.3887	1.0000	0.4498	0.7538	0.8082
Istanbul	1.0000	0.6408	1.0000	1.0000	0.5000	0.5734	0.3685	1.0000	0.1429	0.8233	1.0000	0.7786

Table 4
The Values of S_{ij}

Alternative/ Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
Stockholm	0.3958	0.3667	0.3958	0.3508	0.3806	0.2435	0.3765	0.3386	0.3681	0.2747	0.3379	0.3913
Oslo	0.3325	0.3847	0.3913	0.3780	0.3761	0.3138	0.3780	0.3497	0.2546	0.4015	0.3877	0.4033
Copenhagen	0.3436	0.3843	0.3890	0.4003	0.3538	0.2775	0.4018	0.3654	0.2642	0.3965	0.3500	0.3752
Lahti	0.3040	0.3481	0.3828	0.3271	0.3674	0.3828	0.3128	0.3236	0.2264	0.3480	0.3536	0.3828
London	0.0640	0.0744	0.0980	0.0742	0.0980	0.0625	0.0937	0.0671	0.0879	0.0664	0.0728	0.0717
Berlin	0.0262	0.1859	0.1859	0.2052	0.1859	0.1668	0.2025	0.1783	0.1805	0.2259	0.1805	0.1714
Madrid	0.1663	0.3094	0.3201	0.3357	0.2823	0.2731	0.3472	0.2923	0.2925	0.2678	0.3225	0.3143
Paris	0.1027	0.3093	0.3113	0.3329	0.2948	0.2411	0.3156	0.3073	0.3073	0.3113	0.3223	0.3195
Amsterdam	0.2498	0.3435	0.3463	0.3759	0.2254	0.3339	0.3262	0.3259	0.3074	0.3553	0.3584	0.3557
Istanbul	0.1993	0.3983	0.4015	0.4451	0.3387	0.3641	0.4418	0.3569	0.3031	0.4077	0.3998	0.3996

Table 5
The Final Weights

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
Ej	0.9259	0.2427	0.0041	0.3188	0.7890	0.4960	0.2670	0.6330	0.7845	0.4078	0.2071	0.2377
wj	0.1742	0.0457	0.0008	0.0600	0.1485	0.0934	0.0502	0.1191	0.1476	0.0767	0.0390	0.0447
Rank	1	9	12	7	2	5	8	4	3	6	11	10

The MEREC findings indicated that scope 1 GHG emissions (***C_1***) were the most significant criterion, while particulate air pollution (***C_3***) was the least significant criterion in the assessment of sustainable cities' performance. Moreover, road infrastructure efficiency (***C_5***) and water consumption (***C_9***) were other important criteria for performance evaluation. The overall ranking is as follows: $C_1 > C_5 > C_9 > C_8 > C_6 > C_{10} > C_4 > C_7 > C_2 > C_{12} > C_{11} > C_3$.

4.2. The results obtained from the RAWEC method

The decision matrix (Table 2) presents the maximum and minimum values of each alternative, evaluated against specific criteria. This initial step is crucial as it establishes the groundwork for the normalization process. Subsequently, the decision matrix was subjected to double normalization using Equations (7-8). Criteria weights were determined, and deviations from the maximum normalization values were assessed utilizing Equations (9-10). The final ranking of the alternatives was derived through Equation (11), as demonstrated in Table 6.

Table 6
Final ranking of alternatives (RAWEC)

European Capitals	υ_{ij}	υ'_{ij}	Q_i	Rank
Stockholm	0.2040	0.6930	0.5451	1
Oslo	0.3741	0.6422	0.2638	2
Copenhagen	0.4013	0.6370	0.2270	3
Lahti	0.3811	0.5564	0.1870	4
London	0.4342	0.5719	0.1369	5
Berlin	0.5368	0.4989	-0.0366	7
Madrid	0.5562	0.5403	-0.0145	6
Paris	0.5803	0.3972	-0.1873	8
Amsterdam	0.6579	0.3176	-0.3488	10
Istanbul	0.6344	0.3122	-0.3404	9

The results from the RAWEC indicate that Stockholm, Oslo, and Copenhagen have demonstrated the highest levels of sustainability among cities. In contrast, Paris, Istanbul, and Amsterdam have reported the lowest performance levels. The overall rankings of the cities are as follows: Stockholm > Oslo > Copenhagen > Lahti > London > Madrid > Berlin > Paris > Istanbul > Amsterdam.

4.2. The results obtained from An Extended AROMAN method

Initially, Equations (12-13) were employed to normalize the decision matrix through a double normalization process that combined linear and vector methods. The aggregated average normalization was then computed using Equation (14). Following this, the aggregated average weighted normalized matrix, which encapsulated the various criteria types, was created using Equations (15-17). With the parameter λ set at 0.5, the values for Li and Ai were subsequently determined according to Equations (18-19). Ultimately, the overall ranking of the alternatives was established based on Equation (20), and the results of the Extended AROMAN method are presented in Table 7.

Table 7
Final ranking of alternatives (Extended AROMAN)

European Capitals	$\hat{L_i}$	$\hat{A_i}$	$\hat{L_i}$- $\hat{A_i}$	R_i	*Rank*
Stockholm	0.2232	0.4097	0.1865	1.2050	1
Oslo	0.3024	0.3716	0.0692	1.0716	2
Copenhagen	0.2772	0.3377	0.0605	1.0623	3
Lahti	0.3510	0.3198	-0.0312	0.9693	6
London	0.3595	0.4020	0.0425	1.0434	4
Berlin	0.3827	0.3543	-0.0284	0.9720	5
Madrid	0.3045	0.2593	-0.0452	0.9558	7
Paris	0.3943	0.3028	-0.0915	0.9126	8
Amsterdam	0.4474	0.2328	-0.2146	0.8069	10
Istanbul	0.4023	0.1936	-0.2087	0.8117	9

The results from an Extended AROMAN indicate that Stockholm, Oslo, and Copenhagen have demonstrated the highest levels of sustainability among cities. In contrast, Paris, Istanbul, and Amsterdam have reported the lowest performance levels. The overall rankings of the cities are as follows: Stockholm > Oslo > Copenhagen > London > Berlin > Lahti > Madrid > Paris > Istanbul > Amsterdam.

4.3. The results obtained from the MARA method

The initial normalization of the decision matrix was carried out using Equations (21-22). Following this, the weighted normalized decision matrix was constructed according to Equation (23). Both the normalized and the weighted normalized decision matrices were successfully formulated. The elements corresponding to the optimal alternative were identified through Equations (24-25). Equations (26-27) were employed to calculate the optimal alternative decomposition, while the other alternatives' decompositions were derived using Equations (28-29). The intensity of both the optimal alternative and the remaining options was assessed through Equations (30-33). To identify the areas associated with the optimal alternative and the other options, Equations (34-37) were utilized. The Magnitude of the Area for each alternative was determined using Equation (38). Table 8 summarizes the Magnitude of the Area for all alternatives, along with the final rankings arranged in ascending order of M_i.

Table 8
Final ranking of alternatives (MARA)

Alternative	Magnitude of the Area of Alternative M_i	Values	Rank
Stockholm	M_1	0.0494	1
Oslo	M_2	0.1496	4
Copenhagen	M_3	0.1329	3
Lahti	M_4	0.0764	2
London	M_5	0.3519	10
Berlin	M_6	0.3452	9
Madrid	M_7	0.2109	5
Paris	M_8	0.3060	7
Amsterdam	M_9	0.3126	8
Istanbul	M_{10}	0.2333	6

The results from the MARA indicate that Stockholm, Lahti, and Copenhagen have demonstrated the highest levels of sustainability among cities. In contrast, Amsterdam, Berlin, and London have reported the lowest performance levels. The overall rankings of the cities are as follows: Stockholm > Lahti > Copenhagen > Oslo > Madrid > Istanbul > Paris > Amsterdam > Berlin > London.

4.4. Borda Count results

Following a comprehensive analysis of the sustainable cities' performance of selected European capitals, the Borda counting method was utilized to assess the overall performance of the capitals. The results derived from the Borda Count method are presented in Table 9 and visually represented in Figure 2.

Table 9
Borda Count results

Alternatives	RAWEC		Extended AROMAN		MARA		Borda Count	
	Rank	Score	Rank	Score	Rank	Score	Score	Rank
Stockholm	1	10	1	10	1	10	30	1
Oslo	2	9	2	9	4	7	25	2
Copenhagen	3	8	3	8	3	8	24	3
Lahti	4	7	6	5	2	9	21	4
London	5	6	4	7	10	0	13	6
Berlin	7	4	5	6	9	2	12	7
Madrid	6	5	7	4	5	6	15	5
Paris	8	3	8	3	7	4	10	8
Amsterdam	10	0	10	0	8	3	3	10
Istanbul	9	2	9	2	6	5	9	9

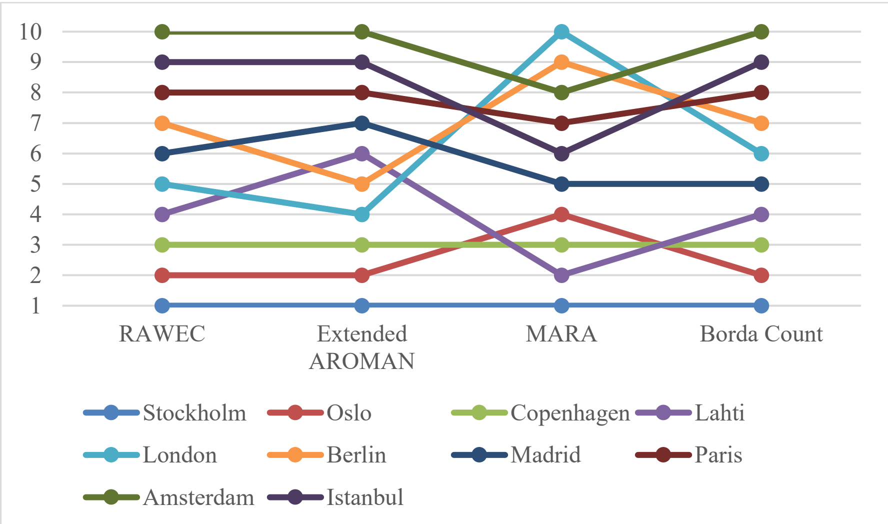

Fig. 2. Comparison of rankings

The Borda count results reveal that Stockholm, Oslo, and Copenhagen consistently rank as the top performers across various methods. Madrid, London, and Berlin maintain consistent standings; although their rankings are not particularly high, they remain solidly established. In contrast, Paris, İstanbul, and Amsterdam typically rank lower in most evaluations. Notably, Amsterdam consistently occupies the bottom position, achieving a Borda score of only 3, which indicates the lowest overall performance.

4.5. Sensitivity Analysis

According to [40], it is crucial to conduct a sensitivity analysis to assess the robustness of research findings. Sensitivity analyses are commonly used to validate results in the MCDM field. This analysis assesses the robustness of the results in light of potential changes in input data, including weights, matrices, methods, and normalization metrics [41]. Moreover, validating these results is crucial for confirming the accuracy and credibility of the proposed model. Given the significant impact of weight coefficients on rankings, this study compared the coefficients obtained with those derived from established weighting techniques such as CRITIC, ENTROPY, and LOPCOW—this comparison aimed to evaluate the significance and reliability of the weight results concerning the hybrid model. The findings from the various weighting methods are presented in Table 10 and visually illustrated in Figure 3.

Table 10
The ranking of the criteria based on different methods

Criteria	MEREC		CRITIC		ENTROPY		LOPCOW	
	Coefficient	Rank	Coefficient	Rank	Coefficient	Rank	Coefficient	Rank
C_1	0.1742	1	0.0755	7	0.2572	1	0.0378	12
C_2	0.0457	9	0.1001	3	0.0121	11	0.0811	7
C_3	0.0008	12	0.0654	10	0.0000	12	0.1259	1
C_4	0.0600	7	0.0962	4	0.0161	9	0.0855	6
C_5	0.1485	2	0.0776	6	0.0621	6	0.0896	5
C_6	0.0934	5	0.1068	2	0.1186	3	0.0727	9
C_7	0.0502	8	0.0616	12	0.0501	7	0.0941	4
C_8	0.1191	4	0.0714	9	0.0966	5	0.1159	2
C_9	0.1476	3	0.1254	1	0.2454	2	0.0947	3
C_{10}	0.0767	6	0.0745	8	0.1116	4	0.0657	10
C_{11}	0.0390	11	0.0636	11	0.0162	8	0.0634	11
C_{12}	0,0447	10	0,0819	5	0,0139	10	0,0736	8

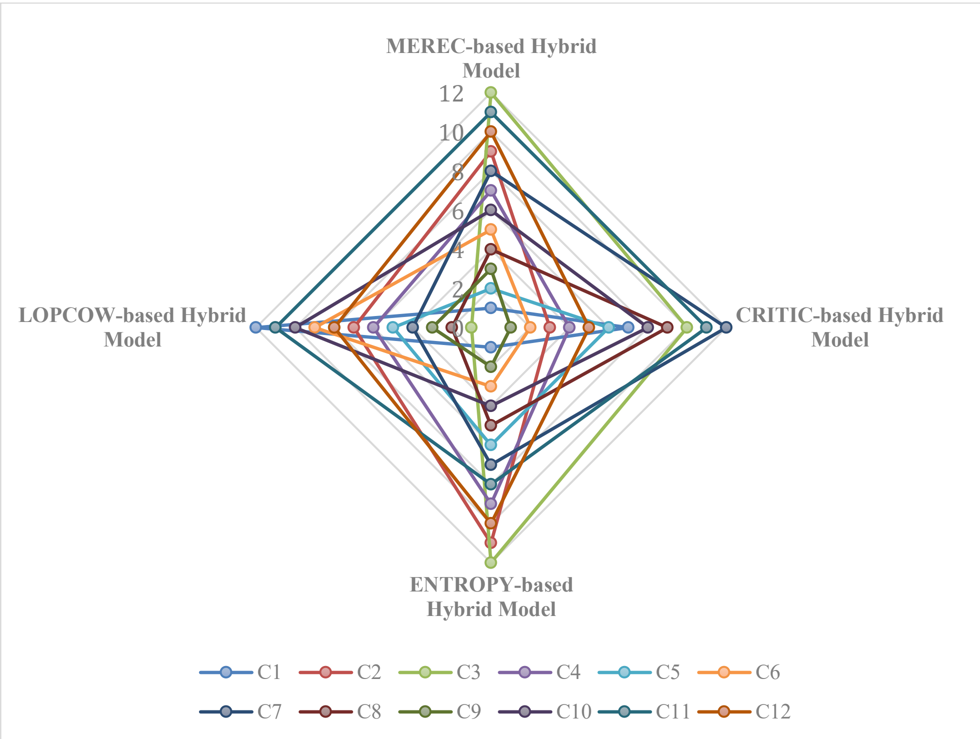

Fig. 3. Comparison of the results of different weighting methods

The findings reveal that the method used for weighting calculations can significantly influence the results. For instance, the MEREC and ENTROPY methods prioritized Scope 1 GHG emissions as the primary criterion. In contrast, alternative approaches such as CRITIC emphasized Water consumption as the key indicator, while LOPCOW highlighted Participatory air pollution in evaluating the performance of sustainable cities. Interestingly, the LOPCOW method identified Participatory air pollution as a crucial indicator, despite it being deemed insignificant by other methods. These results confirm previous studies that pointed out discrepancies between MEREC and LOPCOW, with a notable consistency observed in the ENTROPY method [42]. Thus, the results are closely correlated to the selected weighting method and are quite sensitive to changes in this approach.

5. Discussion and Conclusion

This study investigates the sustainability performance of European capitals, with a specific focus on Stockholm, Oslo, Copenhagen, Lahti, London, Berlin, Madrid, Paris, Amsterdam, and İstanbul, utilizing a hybrid MCDM model. Given that performance evaluations encompass a variety of factors, a hybrid MCDM framework was employed in this research. This paper examines the European capitals, acknowledging their pivotal roles as political and economic centers that shape sustainability policies. Generally, these capitals are characterized by advanced infrastructure, enhanced access to funding, and more effective governance compared to smaller urban areas. Moreover, many cities actively participate in global sustainability initiatives such as the EU Urban Agenda, the European Green Deal, and the SDGs. These factors position them exceptionally well to evaluate sustainability performance. The initial phase of the study involved determining the criteria weights using the MEREC method. The MEREC results indicated that scope 1 GHG emissions were the most critical criterion, whereas particulate air pollution emerged as the least significant criterion in assessing the sustainability performance of cities. Additionally, the efficiency of road infrastructure and water consumption were identified as essential factors influencing the sustainability performance of European capitals. The findings demonstrate that carbon emissions, as well as energy and water efficiency indicators, have a significant impact on performance evaluations. Water conservation is crucial in reducing water consumption, energy usage, and emissions linked to it. These efforts align closely with the United Nations' SDGs, particularly Goals 6 (Clean Water and Sanitation), 7 (Affordable and Clean Energy), 12 (Responsible Consumption and Production), and 13 (Climate Action) [43]. The processes involved in water treatment and distribution are fundamentally dependent on energy consumption, resulting in significant carbon emissions. These emissions significantly contribute to climate change, leading to increased droughts and floods. Such changes have a profound impact on water availability and exacerbate problems related to water scarcity [44]. Furthermore, these results align with prior research [45, 46, 33], which highlights the significant effects of carbon emissions, energy and water efficiency on the performance of sustainable cities.

After establishing the weight of the criteria, the sustainability performance of European capitals was assessed using various Multi-Criteria Decision-Making (MCDM) approaches, including RAWEC, Extended AROMAN, and MARA methods. The findings from the RAWEC method indicate that Stockholm, Oslo, and Copenhagen have achieved the highest levels of sustainability among the cities assessed. Conversely, Paris, Istanbul, and Amsterdam have shown the lowest performance levels. The results from the Extended AROMAN method reflect similar results, with Stockholm, Oslo, and Copenhagen again ranking highest in sustainability. At the same time, Paris, Istanbul, and Amsterdam continue to exhibit the lowest levels of pollution. According to the MARA method, Stockholm, Lahti, and Copenhagen emerged as the leading cities in sustainability performance, whereas Amsterdam, Berlin, and London reported the lowest scores. The Borda count results also affirm that Stockholm, Oslo, and Copenhagen consistently rank as top performers across various assessment methods. The findings suggest that a comparative analysis of sustainability performance—employing RAWEC, Extended AROMAN, and MARA—consistently highlights these cities, particularly within Scandinavia, as leaders in urban sustainability. Robust policy commitments, advanced infrastructure, and practical green initiatives support this achievement. Previous research indicates that Scandinavian cities, such as Stockholm, Oslo, and Copenhagen, are frontrunners in sustainability, primarily due to strategic government initiatives, substantial investments in eco-friendly infrastructure, and a dedicated commitment to sustainable practices. These findings align with studies conducted by [5, 47-49], and 32, which underscore the crucial role of Scandinavian cities in advancing sustainability. In contrast, cities like Paris, Istanbul, and Amsterdam have shown comparatively weaker performance in this regard. Several factors may contribute to these cities' low sustainability performance, including high population density, urban congestion, and governance and planning challenges arising from rapid urbanization and migration. However, this finding contrasts with earlier research by [29], which identified Paris and Amsterdam as having the highest sustainability performance. The observed disparities may be attributed to differences in the indicators used and the calculations associated with the adopted methodological approach.

Sensitivity analysis is frequently employed to evaluate the reliability of results in the MCDM field. This framework assessed a hybrid model through sensitivity analysis to compare its performance with that of several established weighting methods, including CRITIC, ENTROPY, and LOPCOW. The sensitivity analysis results revealed that the selection of the weighting technique can significantly affect the results. Consequently, the findings are closely linked to the selected weighting method and exhibit considerable sensitivity to changes. Based on these insights, we can propose several political and economic implications. Based on these insights, we can propose several political and economic implications:

i. With Scope 1 GHG emissions becoming more significant, policy-makers should prioritize strategic investments and policies to reduce direct emissions from transportation, structures, and industries. Key actions include establishing low-emission zones, promoting the use of electric vehicles, and enhancing energy efficiency in public infrastructure.
ii. Decision-makers should emphasize improving traffic flow, alleviating congestion, and facilitating integrated public transit systems. Implementing advanced traffic control systems and encouraging non-motorized transportation options can improve metropolitan mobility and contribute to sustainability.
iii. Municipal governments should optimize water distribution, minimize leaks, and encourage water-saving technologies. Awareness campaigns can encourage responsible water use in the community.
iv. Municipality executives in underperforming cities like Paris, Istanbul, and Amsterdam can gain insights by comparing their situations with those of top performers such as Stockholm, Oslo, and Copenhagen. This involves conducting case studies, encouraging collaboration, and participating in knowledge-sharing platforms supported by the EU.

It is important to recognize the several limitations of this research; despite the valuable insights it provides into the sustainability performance of ten European capitals. The decision-making model primarily relies on objective evaluation; however, incorporating a subjective approach, such as expert opinions, is crucial for enhancing the model's robustness and validity. Additionally, the study utilized twelve criteria, primarily focusing on environmental factors, but it may not encompass all aspects of performance evaluation. Future research could be significantly enhanced by incorporating additional criteria that consider economic and social dimensions. Furthermore, since this study is limited to the sustainability performance of specific European cities, its findings may not be generalizable to other cities. Lastly, extending the duration of performance evaluations for sustainable cities could yield a more comprehensive understanding of the subject.

Author Contributions

The author has contributed equally to all aspects of the study.

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Data Availability Statement

The research data and supplementary materials are available from the authors upon request.

Conflicts of 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.

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