Published by
NIGERIAN SOCIETY OF PHYSICAL SCIENCES
Available online @ https://journal.nsps.org.ng/index.php/jnsps

J. Nig. Soc. Phys. Sci. 8 (2026) 3644

Journal of the Nigerian Society of Physical Sciences

Medical waste disposal site selection under uncertainty: An interval-valued neutrosophic CRITIC-MARCOS decision support framework

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Abstract

With the ongoing expansion of healthcare services, the amount of medical waste (MW) has been rising steadily, placing increasing pressure on environmental systems and public health. Identifying an appropriate disposal site is challenging because it requires balancing multiple, often conflicting criteria under considerable evaluation uncertainty. This paper develops a hybrid decision-making framework in an interval-valued neutrosophic (IVN) environment by integrating criteria importance through intercriteria correlation (CRITIC) with measurement of alternatives and ranking according to compromise solution (MARCOS). Interval-valued neutrosophic sets represent ambiguity, indeterminacy, and hesitation in expert judgments, while CRITIC derives data-driven criterion weights from aggregated expert evaluations by considering post-deneutrosophication dispersion and inter-criterion conflict. The extended MARCOS method prioritizes alternatives using a utility function that incorporates the ideal and anti-ideal solutions. A secondary-data methodological illustration assesses four candidate locations using nineteen social, economic, environmental, infrastructural, and geological criteria. Comparisons with IVN-TOPSIS, IVN-MAIRCA, IVN-EDAS, and IVN-VIKOR show that all five frameworks identify the same first-ranked site, whereas the ordering of the remaining alternatives is method-sensitive. These comparisons are interpreted at the integrated-framework level because the benchmark methods retain their own weighting and ranking mechanisms.

DOI: 10.46481/jnsps.2026.3644

Keywords: Interval-valued neutrosophic sets, CRITIC, MARCOS, Decision-making, Medical waste disposal

Article History:
Received: 27 June 2026
Received in revised form: 03 August 2026
Accepted for publication: 20 August 2026
Available online: 24 September 2026

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1. Introduction

The continuous expansion of global healthcare demand has driven steady growth in medical waste (MW) production. The waste produced by modern medical facilities has a highly complex composition, including infectious and pathological materials and various harmful chemicals, which distinguishes it from traditional municipal solid waste [1, 2]. These wastes contain pathogens and toxic chemicals that pose significant risks to ecosystems and public health [3, 4]. The World Health Organization (WHO) and national environmental protection agencies around the world have officially listed MW as hazardous waste. Therefore, developing a safe disposal system to protect the local ecosystem is an indispensable part of sustainable urban infrastructure development.

Among all components of the safe MW management system, the design of effective and safe final disposal facilities remains a key priority for disease control and prevention of secondary environmental disasters. High-temperature incineration currently stands as the leading global treatment method for MW. Although incineration can effectively eliminate pathogens and greatly reduce waste volume, it requires strict operation and management. Poorly managed incinerators can discharge highly toxic gases [5], most notably dioxins and furans, and can leave concentrated heavy metals, including copper, zinc, lead, and cadmium, in bottom-ash residue. This secondary pollution can seriously and persistently damage air, surface water, groundwater, and soil ecosystems and pose a serious threat to the surrounding communities and natural environment.

To mitigate these severe risks, proper site selection serves as a crucial defense mechanism. However, in densely populated areas, this process involves fierce conflicts between different stakeholders. Municipalities mainly seek to minimize costs and optimize infrastructure. By contrast, environmental agencies implement strict regulations to ensure compliance with permissible emission standards and rigorous environmental-protection requirements throughout the life cycle of facilities [2]. In addition, due to health and safety issues, residents often oppose nearby construction, creating social conflict that can derail feasible projects. Therefore, determining the optimal location for centralized disposal of MW is not only an engineering task subject to strict regulations [6], but also a complex decision-making challenge that requires coordination of economic constraints, ecological security, and public acceptance.

Because simultaneously satisfying economic, environmental, and social requirements involves navigating complex trade-offs, waste facility siting constitutes a highly complex decision problem. Consequently, multi-criteria decision-making (MCDM) methods have been widely applied for selecting optimal disposal locations, particularly for highly hazardous MW [7]. MCDM provides a structured basis for evaluating alternatives and resolving complex, conflicting demands [8, 9].

Over the past decade, a variety of MCDM techniques have been widely deployed to resolve such complex evaluations [10–12]. Beyond waste management, MCDM has also been applied across engineering to support material selection and the adoption of green technologies in industrial sectors [13, 14]. For example, a new method combining the analytic hierarchy process and the standard scoring method has recently been developed to robustly assess and determine the geographical area most suitable for the establishment of manufacturing facilities [15]. Additionally, MCDM has been used to support sustainable wind-energy planning in areas with complex topographical constraints, aiding energy planners and policymakers [16].

1.1. Motivation and contributions

While MCDM has been widely used to solve these problems, its practical application faces a major challenge: the inherent fuzziness and uncertainty of evaluation data. When experts evaluate candidate sites according to qualitative and highly sensitive criteria such as social acceptance and environmental risk, they rarely have absolute certainty. To mathematically model this human uncertainty, traditional fuzzy sets (FS) were first introduced to capture continuous degrees of truth [17]. Subsequently, intuitionistic fuzzy sets (IFS) extended this framework by introducing a non-membership parameter to represent simultaneous acceptance and rejection [18]. However, the sum of membership and non-membership in IFS is limited to less than or equal to 1, so hesitation is treated as a residual quantity. The practical applicability of IFSs has also been strengthened through improved distance measures, which provide more reliable discrimination between intuitionistic fuzzy information and have been applied to pattern recognition and medical diagnosis [19]. For instance, novel parametric intuitionistic fuzzy entropy measures have recently been developed to enhance image edge detection, significantly improving structural boundary localization for advanced pattern recognition [20].

To overcome these limitations, advanced fuzzy extensions have been heavily explored, particularly within medical science and healthcare, where clinical imprecision is pervasive. For example, tendency coefficient–driven Pythagorean fuzzy distance approaches have been recently developed to tackle complex selection problems in MW management [21], evaluate competing criteria in healthcare services [22], and improve precision in pattern classification and disease diagnostic analysis [23]. To accommodate even greater multidimensional uncertainty, researchers have successfully applied Fermatean fuzzy distance models to predict glaucoma risks based on complex clinical data [24], and introduced novel q-rung orthopair fuzzy techniques to robustly assess patient severity during medical examinations [25]. Similarly, fractional q-rung picture fuzzy hypersoft sets have been integrated with trigonometric similarity measures to further enhance pattern recognition and complex decision-making [26].

While these extensions provide significant adaptability, managing interval-based uncertainty remains critical. Interval-valued intuitionistic fuzzy sets (IVIFS) were later introduced to address the problem that a single value is not enough to represent these degrees [27]. Although IVIFS improves the flexibility of value expression, it retains the basic limitation of IFS: hesitation is still a dependent variable rather than an independent dimension. In the highly polarized environment of MW site selection, conflicting interests among government, environmental agencies, and residents can create substantial uncertainty and differences in expert judgment. However, an IVIFS often fails to fully capture this complexity because it treats hesitation merely as a dependent remainder. It cannot explicitly distinguish between indeterminacy, which represents the inability to determine a degree of truth or falsity due to missing or incomplete information, and conflicting evidence, where independent sources simultaneously provide high truth and high falsity.

To solve this key limitation, neutrosophic sets (NS) provide a more complex logical framework, which explicitly characterizes truth, indeterminacy, and falsity as three independent dimensions [28]. Among many NS extensions, the single-valued neutrosophic set (SVNS) is the most widely used in practical decision-making [29]. SVNS-based MCDM has been applied to renewable energy resource selection under uncertain, indeterminate, and inconsistent information [30]. Beyond these applications, neutrosophic MCDM has also been applied to environmental and resource-management problems, where bipolar neutrosophic representations allow positive and negative decision information to be considered simultaneously, as demonstrated in water resource management [31]. Furthermore, advanced neutrosophic paradigms and their parametric, hypersoft, and complex topological extensions have recently demonstrated capabilities in complex data representation and AI-assisted analysis [32]. For instance, novel Hellinger divergence measures under neutrosophic hypersoft sets have been formulated for the symptomatic detection of COVID-19 [33], and parametric neutrosophic discriminant measures have been successfully utilized to resolve intricate medical diagnosis problems [34].

However, the practical use of SVNSs can impose considerable elicitation demands. In complex problems such as MW facility siting, experts may be required to specify precise numerical values for three independent components, which can be cognitively demanding and difficult to justify in practice. To provide a more flexible representation, these concepts are extended to interval-valued neutrosophic sets (IVNS) [35]. IVNSs use interval bounds rather than fixed single values, allowing decision-makers to express evaluations as ranges and effectively capture the inherent fuzziness of data in controversial spatial evaluation.

In recent years, IVN methods have received increasing attention in complex infrastructure and engineering decision-making problems. Related interval-neutrosophic extensions have also demonstrated their applicability in healthcare decision-making. In the evaluation of smartphone applications for obesity management, an interval neutrosophic vague framework has been employed to integrate criterion weighting and alternative ranking while accommodating imprecise and incomplete evaluation information [36]. For instance, researchers have used IVN methods to address inconsistent expert judgments in medical environments and have developed IVN-AHP fuzzy-inference-system methods to assess the fire safety risk of medical facilities [37]. Similarly, in critical engineering sectors, a framework integrating IVN-AHP, IVN-CoCoSo, and IVN-HOQ methods has been developed to evaluate occupational health and safety hazards during construction site excavations [38]. IVNS has also been applied in spatial decision-making, with the IVN-TOPSIS method used to manage conflicting variables and optimize location selection for international education fairs [39]. Building on this mathematical evolution, this study adopts the IVNS framework, as it effectively accommodates the extreme complexity and multidimensional indeterminacy inherent in evaluating competing MW disposal sites.

Once evaluation uncertainty is represented through IVNS, a second methodological challenge concerns the determination of criterion weights without direct subjective assignment. Subjective weighting methods such as the analytic hierarchy process (AHP), best-worst method (BWM), and step-wise weight assessment ratio analysis (SWARA) rely directly on expert preferences, while criteria importance through intercriteria correlation (CRITIC) derives criterion weights from the information contained in the decision matrix. Specifically, CRITIC considers both criterion dispersion and inter-criterion conflict, thereby providing a data-driven basis for criterion weighting. This weighting mechanism has been applied in many areas, including the risk assessment of sustainable supply chains in the petrochemical industry [40], the safety assessment of transportation infrastructure [41], the prioritization of renewable energy [42], and the risk assessment of enterprise internal control [43].

After criterion weighting, the next stage is to develop a ranking process that evaluates alternatives relative to both the ideal solution (AI) and anti-ideal solution (AAI). Traditional ranking methods, such as TOPSIS, COPRAS, VIKOR, and PROMETHEE II, may exhibit rank reversals when the composition of the alternative set changes [44, 45]. Recent efforts have enhanced traditional architectures, such as the VIKOR method, to better aggregate complex and uncertain information in hesitant fuzzy environments [46]. However, there are still vulnerabilities related to dynamic changes in alternatives. To address this issue, this study adopts the measurement of alternatives and ranking according to compromise solution (MARCOS) method to establish a dual-reference evaluation framework. MARCOS uses AI and AAI reference points simultaneously to construct its utility function, thereby providing a dual-reference basis for alternative evaluation [47]. In this study, this mechanism is used to provide a dual-reference evaluation structure for alternative ranking.

MARCOS and its fuzzy extensions have been widely applied in complex multidimensional decision-making. In content-centric networking, q-rung orthopair fuzzy MARCOS has been employed to evaluate cache placement policies under complex group preference information [48]. The IVIFS-MARCOS method has also been used to select sustainable equipment suppliers for organ-transplantation networks [49]. In urban infrastructure, the SVNS-MARCOS method has been used to prioritize sustainable hybrid vehicles in intelligent urban planning [50]. An IVN-MARCOS framework has also been developed to assess the decarbonization goals of sustainable aviation fuel suppliers [51]. These applications illustrate the compatibility of MARCOS with neutrosophic decision environments.

Based on the above considerations, this study develops an integrated IVN-CRITIC-MARCOS decision-support framework to address key challenges in MW disposal site selection, including uncertainty representation, data-driven criterion weighting, and alternative ranking. The proposed framework combines the capability of IVNS to model ambiguous and indeterminate evaluation information, the CRITIC method for deriving conflict-aware, data-driven criterion weights, and the MARCOS approach for evaluating alternatives relative to AI and AAI reference solutions. The applicability of the proposed framework is further examined through a case-based evaluation. The main contributions of this study can be summarized as follows:

An IVN decision representation scheme is established for MW disposal site selection, allowing ambiguous, incomplete, and conflicting expert evaluations to be simultaneously characterized through truth, indeterminacy, and falsity dimensions.

In addition, A conflict-aware IVN-CRITIC weighting mechanism is developed to determine criterion importance from the intrinsic information of the aggregated decision matrix, considering both criterion variability and inter-criterion conflict without requiring subjective weight assignment.

The framework also an IVN-MARCOS ranking strategy is integrated with the proposed weighting mechanism by employing AI and AAI reference solutions, thereby providing a comprehensive evaluation framework for competing alternatives under uncertainty.

Finally, The proposed framework is demonstrated through a MW disposal site selection case involving nineteen criteria and four candidate locations, illustrating its applicability in complex spatial decision-making scenarios.

2. Basic concepts

This section presents some basic mathematical concepts.

Definition 1 ([17]). *Let $\mathfrak{D} = \{\mathfrak{d}_1, \mathfrak{d}_2, \ldots, \mathfrak{d}_n\}$ be a universe of discourse (UOD). The FS $\mathcal{R}$ in $\mathfrak{D}$ is defined as*

$$\mathcal{R} = \{\langle \mathfrak{d}_i, \mu_{\mathcal{R}}(\mathfrak{d}_i)\rangle \mid \mathfrak{d}_i \in \mathfrak{D}\}, \tag{1}$$

where $\mu_{\mathcal{R}}(\mathfrak{d}_i) \in [0,1]$ represents the membership degree.

Definition 2 ([18]). *The IFS $\mathcal{R}$ in $\mathfrak{D}$ is defined as:*

$$\mathcal{R} = \{\langle \mathfrak{d}_i, \mu_{\mathcal{R}}(\mathfrak{d}_i), \nu_{\mathcal{R}}(\mathfrak{d}_i)\rangle \mid \mathfrak{d}_i \in \mathfrak{D}\}, \tag{2}$$

where $\mu_{\mathcal{R}}(\mathfrak{d}_i), \nu_{\mathcal{R}}(\mathfrak{d}_i) \in [0,1]$ express the membership and non-membership degrees, satisfying $0 \leqslant \mu_{\mathcal{R}}(\mathfrak{d}_i) + \nu_{\mathcal{R}}(\mathfrak{d}_i) \leqslant 1$. The hesitancy degree is defined as $\pi_{\mathcal{R}}(\mathfrak{d}_i) = 1 - \mu_{\mathcal{R}}(\mathfrak{d}_i) - \nu_{\mathcal{R}}(\mathfrak{d}_i)$.

Definition 3 ([27]). *An IVIFS $\mathcal{R}$ in $\mathfrak{D}$ is formulated as:*

$$\mathcal{R} = \left\{\left\langle \mathfrak{d}_i, \left[\mu^L_{\mathcal{R}}(\mathfrak{d}_i), \mu^U_{\mathcal{R}}(\mathfrak{d}_i)\right], \left[\nu^L_{\mathcal{R}}(\mathfrak{d}_i), \nu^U_{\mathcal{R}}(\mathfrak{d}_i)\right]\right\rangle \mid \mathfrak{d}_i \in \mathfrak{D}\right\}, \tag{3}$$

where the intervals satisfy $0 \leqslant \mu^L_{\mathcal{R}}(\mathfrak{d}_i) \leqslant \mu^U_{\mathcal{R}}(\mathfrak{d}_i) \leqslant 1$, $0 \leqslant \nu^L_{\mathcal{R}}(\mathfrak{d}_i) \leqslant \nu^U_{\mathcal{R}}(\mathfrak{d}_i) \leqslant 1$, and the sum of the upper boundaries strictly satisfies $0 \leqslant \mu^U_{\mathcal{R}}(\mathfrak{d}_i) + \nu^U_{\mathcal{R}}(\mathfrak{d}_i) \leqslant 1$.

Definition 4 ([29]). *An SVNS $\mathcal{R}$ in $\mathfrak{D}$ is defined as:*

$$\mathcal{R} = \{\langle \mathfrak{d}_i, T_{\mathcal{R}}(\mathfrak{d}_i), I_{\mathcal{R}}(\mathfrak{d}_i), F_{\mathcal{R}}(\mathfrak{d}_i)\rangle \mid \mathfrak{d}_i \in \mathfrak{D}\}, \tag{4}$$

where $T_{\mathcal{R}}(\mathfrak{d}_i), I_{\mathcal{R}}(\mathfrak{d}_i), F_{\mathcal{R}}(\mathfrak{d}_i) \in [0,1]$. Given any $\mathfrak{d}_i \in \mathfrak{D}$, it follows that $0 \leqslant T_{\mathcal{R}}(\mathfrak{d}_i) + I_{\mathcal{R}}(\mathfrak{d}_i) + F_{\mathcal{R}}(\mathfrak{d}_i) \leqslant 3$.

Definition 5 ([35]). *An IVNS $\mathcal{R}$ in $\mathfrak{D}$ is defined as follows:*

$$\mathcal{R} = \left\{\left\langle \mathfrak{d}_i, \left[T^L_{\mathcal{R}}(\mathfrak{d}_i), T^U_{\mathcal{R}}(\mathfrak{d}_i)\right], \left[I^L_{\mathcal{R}}(\mathfrak{d}_i), I^U_{\mathcal{R}}(\mathfrak{d}_i)\right], \left[F^L_{\mathcal{R}}(\mathfrak{d}_i), F^U_{\mathcal{R}}(\mathfrak{d}_i)\right]\right\rangle \,\middle|\, \mathfrak{d}_i \in \mathfrak{D}\right\}, \tag{5}$$

where $0 \leqslant T^L_{\mathcal{R}}(\mathfrak{d}_i) \leqslant T^U_{\mathcal{R}}(\mathfrak{d}_i) \leqslant 1$, $0 \leqslant I^L_{\mathcal{R}}(\mathfrak{d}_i) \leqslant I^U_{\mathcal{R}}(\mathfrak{d}_i) \leqslant 1$, and $0 \leqslant F^L_{\mathcal{R}}(\mathfrak{d}_i) \leqslant F^U_{\mathcal{R}}(\mathfrak{d}_i) \leqslant 1$. The sum of the upper boundaries strictly satisfies $0 \leqslant T^U_{\mathcal{R}}(\mathfrak{d}_i) + I^U_{\mathcal{R}}(\mathfrak{d}_i) + F^U_{\mathcal{R}}(\mathfrak{d}_i) \leqslant 3$.

Definition 6 ([52]). *To compare interval-valued neutrosophic numbers (IVNNs) or transform them into crisp values, this study uses the following deneutrosophication mapping consistently throughout the CRITIC and MARCOS calculations. For $\tilde{\xi} = \langle [T^L, T^U], [I^L, I^U], [F^L, F^U]\rangle$,*

$$\Psi(\tilde{\xi}) = \frac{T^L + T^U}{2} + I^U\left(1 - \frac{I^L + I^U}{2}\right) - (1 - F^U)\left(\frac{F^L + F^U}{2}\right). \tag{6}$$

Definition 7 ([53]). *Let $\tilde{\xi}_k$ $(k = 1, 2, \ldots, l)$ be a collection of IVNNs, and $\boldsymbol{\lambda} = \{\lambda_1, \ldots, \lambda_l\}$ be their corresponding weight vector such that $\lambda_k \in [0,1]$ and $\sum_{k=1}^{l} \lambda_k = 1$. The interval neutrosophic weighted arithmetic averaging (INWAA) operator is defined as:*

$$INWAA_\lambda(\tilde{\xi}_1, \ldots, \tilde{\xi}_l) = \bigoplus_{k=1}^{l} \lambda_k \tilde{\xi}_k = \left\langle \begin{array}{c} \left[1 - \prod_{k=1}^{l}(1 - T^L_k)^{\lambda_k}, \quad 1 - \prod_{k=1}^{l}(1 - T^U_k)^{\lambda_k}\right], \\ \left[\prod_{k=1}^{l}(I^L_k)^{\lambda_k}, \prod_{k=1}^{l}(I^U_k)^{\lambda_k}\right], \left[\prod_{k=1}^{l}(F^L_k)^{\lambda_k}, \prod_{k=1}^{l}(F^U_k)^{\lambda_k}\right] \end{array} \right\rangle. \tag{7}$$

Definition 8 ([37]). *Let $\tilde{\xi}_1 = ([T^L_1, T^U_1], [I^L_1, I^U_1], [F^L_1, F^U_1])$ and $\tilde{\xi}_2 = ([T^L_2, T^U_2], [I^L_2, I^U_2], [F^L_2, F^U_2])$ be two IVNNs, and let $\lambda > 0$ be a scalar. The basic algebraic operations are defined as follows:*

1. $\tilde{\xi}_1 \oplus \tilde{\xi}_2 = \begin{pmatrix} [T^L_1 + T^L_2 - T^L_1 T^L_2, T^U_1 + T^U_2 - T^U_1 T^U_2], \\ [I^L_1 I^L_2, I^U_1 I^U_2], [F^L_1 F^L_2, F^U_1 F^U_2] \end{pmatrix}$.
2. $\tilde{\xi}_1 \otimes \tilde{\xi}_2 = \begin{pmatrix} [T^L_1 T^L_2, T^U_1 T^U_2], \\ [I^L_1 + I^L_2 - I^L_1 I^L_2, I^U_1 + I^U_2 - I^U_1 I^U_2], \\ [F^L_1 + F^L_2 - F^L_1 F^L_2, F^U_1 + F^U_2 - F^U_1 F^U_2] \end{pmatrix}$.
3. $\lambda\tilde{\xi}_1 = \begin{pmatrix} [1 - (1 - T^L_1)^\lambda, 1 - (1 - T^U_1)^\lambda], \\ [(I^L_1)^\lambda, (I^U_1)^\lambda], [(F^L_1)^\lambda, (F^U_1)^\lambda] \end{pmatrix}$.
4. $\tilde{\xi}_1^\lambda = \begin{pmatrix} [(T^L_1)^\lambda, (T^U_1)^\lambda], \\ [1 - (1 - I^L_1)^\lambda, 1 - (1 - I^U_1)^\lambda], \\ [1 - (1 - F^L_1)^\lambda, 1 - (1 - F^U_1)^\lambda] \end{pmatrix}$.

3. Proposed hybrid decision-making framework

This section formulates a hybrid decision-making framework tailored to address the inherent complexities and uncertainties in MCDM problems. The proposed framework comprises three sequential phases. First, linguistic evaluation information provided by experts is normalized and mapped into IVNNs. Subsequently, individual decision matrices are aggregated using the INWAA operator coupled with a deneutrosophication function. Second, the IVN-CRITIC method is applied to derive the CRITIC criterion weights. Finally, an extended MARCOS method is employed to generate the final ranking of the available alternatives. The flowchart of the proposed framework is shown in Figure 1.

Phase 1 Construct the aggregated decision matrix.

Step 1: Let $\mathcal{S} = \{\mathcal{S}_1, \ldots, \mathcal{S}_m\}$ be a set of m alternatives, $\mathcal{C} = \{C_1, \ldots, C_n\}$ be n criteria, and $\mathcal{E} = \{\mathcal{E}_1, \ldots, \mathcal{E}_l\}$ be l experts. The experts' linguistic evaluations are transformed into IVNNs using the linguistic terms. The initial decision matrix of the k-th expert is $\Xi_k = [\tilde{\xi}_{ij}^{(k)}]_{m\times n}$:

$$\Xi_k = \begin{bmatrix} \tilde{\xi}_{11}^{(k)} & \cdots & \tilde{\xi}_{1j}^{(k)} & \cdots & \tilde{\xi}_{1n}^{(k)} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{\xi}_{i1}^{(k)} & \cdots & \tilde{\xi}_{ij}^{(k)} & \cdots & \tilde{\xi}_{in}^{(k)} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{\xi}_{m1}^{(k)} & \cdots & \tilde{\xi}_{mj}^{(k)} & \cdots & \tilde{\xi}_{mn}^{(k)} \end{bmatrix}, \tag{8}$$

where $\tilde{\xi}_{ij}^{(k)} = \left\langle \left[T_{ij}^{L(k)}, T_{ij}^{U(k)}\right], \left[I_{ij}^{L(k)}, I_{ij}^{U(k)}\right], \left[F_{ij}^{L(k)}, F_{ij}^{U(k)}\right] \right\rangle$ denotes the evaluation of alternative $\mathcal{S}_i$ under criterion C_j by expert $\mathcal{E}_k$.

Step 2: Let $\boldsymbol{\lambda} = \{\lambda_1, \ldots, \lambda_l\}$ be the expert weight vector ($\sum_{k=1}^{l} \lambda_k = 1$). The individual assessments are aggregated using the INWAA operator to form the aggregated decision matrix $\Xi = [\tilde{\xi}_{ij}]_{m\times n}$:

$$\begin{aligned} \tilde{\xi}_{ij} &= INWAA_{\lambda}\left(\tilde{\xi}_{ij}^{(1)}, \tilde{\xi}_{ij}^{(2)}, \ldots, \tilde{\xi}_{ij}^{(l)}\right) \\ &= \left\langle \left[1 - \prod_{k=1}^{l}\left(1 - T_{ij}^{L(k)}\right)^{\lambda_k}, 1 - \prod_{k=1}^{l}\left(1 - T_{ij}^{U(k)}\right)^{\lambda_k}\right], \right. \\ &\quad \left[\prod_{k=1}^{l}\left(I_{ij}^{L(k)}\right)^{\lambda_k}, \prod_{k=1}^{l}\left(I_{ij}^{U(k)}\right)^{\lambda_k}\right], \\ &\quad \left. \left[\prod_{k=1}^{l}\left(F_{ij}^{L(k)}\right)^{\lambda_k}, \prod_{k=1}^{l}\left(F_{ij}^{U(k)}\right)^{\lambda_k}\right] \right\rangle . \end{aligned} \tag{9}$$

Phase 2 Calculate the criteria weights.

Step 3: For the CRITIC method, the aggregated matrix Ξ is transformed into a crisp score matrix $S = [s_{ij}]_{m\times n}$ via the deneutrosophication mapping function in Eq. (6):

$$s_{ij} = \Psi(\tilde{\xi}_{ij}). \tag{10}$$

Step 4: The crisp matrix S is normalized to eliminate dimensional influences according to benefit (B) and cost (C) criteria, yielding the standard matrix $N = [n_{ij}]_{m\times n}$:

$$n_{ij} = \begin{cases} \dfrac{s_{ij} - \min_i s_{ij}}{\max_i s_{ij} - \min_i s_{ij}}, & \text{if } C_j \in B \\ \dfrac{\max_i s_{ij} - s_{ij}}{\max_i s_{ij} - \min_i s_{ij}}, & \text{if } C_j \in C \end{cases}. \tag{11}$$

To prevent undefined operations when all alternatives share identical scores for a specific criterion, a zero-variance handling rule is explicitly specified. Under this rule, if the maximum and minimum evaluation scores are strictly equal, yielding a zero denominator, the normalized value is directly and uniformly assigned 1 to reflect equivalent maximal performance across all alternatives. However, this exception was not triggered in the current empirical case since expert evaluations exhibited natural variations.

Step 5: The standard deviation σ_j for each criterion is calculated:

$$\sigma_j = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}\left(n_{ij} - \bar{n}_j\right)^2}, \tag{12}$$

where $\bar{n}_j = \frac{1}{m}\sum_{i=1}^{m} n_{ij}$ is the mean normalized score.

Step 6: The conflict between criteria is measured by the linear correlation coefficient ρ_{jp}:

$$\rho_{jp} = \frac{\sum_{i=1}^{m}(n_{ij} - \bar{n}_j)(n_{ip} - \bar{n}_p)}{\sqrt{\sum_{i=1}^{m}(n_{ij} - \bar{n}_j)^2 \sum_{i=1}^{m}(n_{ip} - \bar{n}_p)^2}}. \tag{13}$$

Step 7: Determine the CRITIC weight w_j by normalizing the criterion information quantity Q_j:

$$w_j = \frac{Q_j}{\sum_{j=1}^{n} Q_j}, \tag{14}$$

where $Q_j = \sigma_j \sum_{p=1}^{n}(1 - \rho_{jp})$.

Phase 3 Evaluate and rank the alternatives.

Step 8: For the extended MARCOS method, the AI and AAI solutions are defined as reference points $\tilde{\xi}_{AI,j}$ and $\tilde{\xi}_{AAI,j}$:

$$\tilde{\xi}_{AI,j} = \begin{cases} \left\langle \begin{matrix} \left[\max_i T_{ij}^{L}, \max_i T_{ij}^{U}\right], \\ \left[\min_i I_{ij}^{L}, \min_i I_{ij}^{U}\right], \\ \left[\min_i F_{ij}^{L}, \min_i F_{ij}^{U}\right] \end{matrix} \right\rangle, & \text{if } C_j \in B \\ \left\langle \begin{matrix} \left[\min_i T_{ij}^{L}, \min_i T_{ij}^{U}\right], \\ \left[\max_i I_{ij}^{L}, \max_i I_{ij}^{U}\right], \\ \left[\max_i F_{ij}^{L}, \max_i F_{ij}^{U}\right] \end{matrix} \right\rangle, & \text{if } C_j \in C \end{cases}, \tag{15}$$

$$\tilde{\xi}_{AAI,j} = \begin{cases} \left\langle \begin{matrix} \left[\min_i T_{ij}^{L}, \min_i T_{ij}^{U}\right], \\ \left[\max_i I_{ij}^{L}, \max_i I_{ij}^{U}\right], \\ \left[\max_i F_{ij}^{L}, \max_i F_{ij}^{U}\right] \end{matrix} \right\rangle, & \text{if } C_j \in B \\ \left\langle \begin{matrix} \left[\max_i T_{ij}^{L}, \max_i T_{ij}^{U}\right], \\ \left[\min_i I_{ij}^{L}, \min_i I_{ij}^{U}\right], \\ \left[\min_i F_{ij}^{L}, \min_i F_{ij}^{U}\right] \end{matrix} \right\rangle, & \text{if } C_j \in C \end{cases}. \tag{16}$$

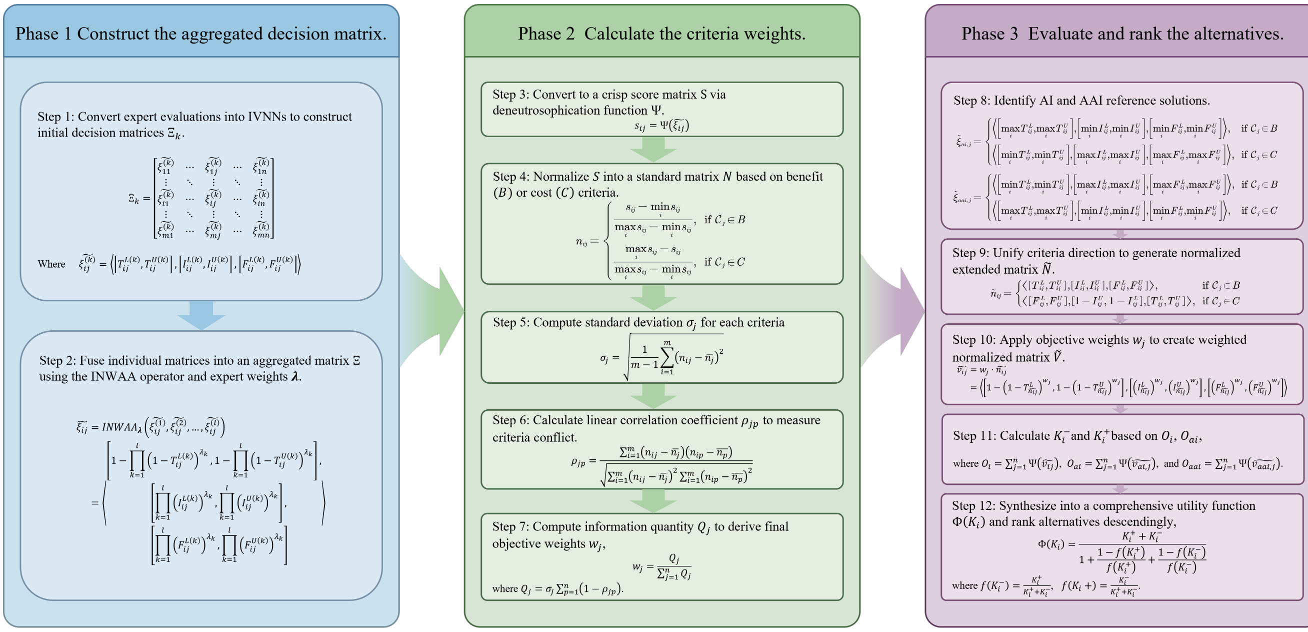

Figure 1: Flowchart of the proposed model.

The extrema are taken componentwise so that the truth, indeterminacy, and falsity intervals retain their respective roles. Because all selected endpoints remain in [0, 1] and each lower endpoint does not exceed its corresponding upper endpoint, the constructed reference points satisfy the IVNN endpoint conditions used in this study.

Step 9: The extended decision matrix is normalized to $\tilde{N} = [\tilde{n}_{ij}]_{(m+2)\times n}$. To unify criteria into a beneficial direction and avoid risks of division by zero, the neutrosophic complement is applied to cost criteria:

$$\tilde{n}_{ij} = \begin{cases} \left\langle \begin{array}{c} [T_{ij}^L, T_{ij}^U],\ [I_{ij}^L, I_{ij}^U], \\ [F_{ij}^L, F_{ij}^U] \end{array} \right\rangle, & C_j \in B, \\ \left\langle \begin{array}{c} [F_{ij}^L, F_{ij}^U],\ [1-I_{ij}^U, 1-I_{ij}^L], \\ [T_{ij}^L, T_{ij}^U] \end{array} \right\rangle, & C_j \in C. \end{cases} \tag{17}$$

This normalization is concurrently applied to the AI and AAI solutions. Following the IVN-MARCOS implementation in [51], cost criteria are transformed by the neutrosophic complement before weighting. This approach avoids direct interval division and preserves endpoint ordering under the stated transformation.

Step 10: The weighted normalized IVN matrix $\tilde{V} = [\tilde{v}_{ij}]_{(m+2)\times n}$ is computed using scalar multiplication with the CRITIC weights w_j:

$$\begin{aligned} \tilde{v}_{ij} &= w_j \cdot \tilde{n}_{ij} \\ &= \left\langle \begin{array}{c} \left[1-(1-T_{\tilde{n}_{ij}}^L)^{w_j}, 1-(1-T_{\tilde{n}_{ij}}^U)^{w_j}\right], \\ \left[(I_{\tilde{n}_{ij}}^L)^{w_j}, (I_{\tilde{n}_{ij}}^U)^{w_j}\right], \\ \left[(F_{\tilde{n}_{ij}}^L)^{w_j}, (F_{\tilde{n}_{ij}}^U)^{w_j}\right] \end{array} \right\rangle. \end{aligned} \tag{18}$$

Step 11: The weighted normalized IVNNs are deneutrosophicated following Step 3 to compute the summation scores O_i, O_{ai}, and O_{aai}. Subsequently, the utility degrees K_i^- and K_i^+ are calculated as:

$$K_i^- = \frac{O_i}{O_{aai}}, \quad K_i^+ = \frac{O_i}{O_{ai}}, \tag{19}$$

where $O_i = \sum_{j=1}^n \Psi(\tilde{v}_{ij})$, $O_{ai} = \sum_{j=1}^n \Psi(\tilde{v}_{AI,j})$, and $O_{aai} = \sum_{j=1}^n \Psi(\tilde{v}_{AAI,j})$.

Step 12: The comprehensive utility function $\Phi(K_i)$ is synthesized:

$$\Phi(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1-f(K_i^+)}{f(K_i^+)} + \frac{1-f(K_i^-)}{f(K_i^-)}}, \tag{20}$$

where $f(K_i^+)$ represents the utility function concerning the AI solution, while $f(K_i^-)$ denotes the utility function with the AAI solution, which are determined as:

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-}, \quad f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-}. \tag{21}$$

The cross-dependent expressions in Eq. (20) follow the original MARCOS formulation of Stević *et al.* [47].

Finally, alternatives are ranked in descending order by their comprehensive utility value $\Phi(K_i)$. The highest $\Phi(K_i)$ represents the optimal choice.

The detailed computational procedure of the proposed framework is summarized in Algorithm 1.

4. Illustrative case study

4.1. Background statement

To examine the computational applicability of the proposed IVN-CRITIC-MARCOS framework, this study uses a

Algorithm 1: Proposed hybrid decision-making framework.

Input: Alternatives $\mathcal{S} = \{\mathcal{S}_1, \ldots, \mathcal{S}_m\}$, Criteria $C = \{C_1, \ldots, C_n\}$, Experts $\mathcal{E} = \{\mathcal{E}_1, \ldots, \mathcal{E}_l\}$, Linguistic terms.
Output: Ranking of alternatives.
Phase 1: Construct the aggregated decision matrix
Step 1: Transform experts' linguistic evaluations into IVNNs to form the initial decision matrix $\Xi_k = [\tilde{\xi}_{ij}^{(k)}]_{m\times n}$.
Step 2: Aggregate individual assessments into decision matrix $\Xi = [\tilde{\xi}_{ij}]_{m\times n}$ using the INWAA operator via Eq. (9).
Phase 2: Calculate the criteria weights
Step 3: Transform the aggregated matrix into a crisp score matrix $S = [s_{ij}]_{m\times n}$ via the deneutrosophication mapping Eq. (6).
Step 4: Normalize crisp matrix S to yield the standard matrix $N = [n_{ij}]_{m\times n}$ via Eq. (11).
Step 5: Calculate the standard deviation σ_j for each criterion via Eq. (12).
Step 6: Measure the conflict between criteria using the linear correlation coefficient ρ_{jp} via Eq. (13).
Step 7: Calculate the information quantity Q_j and determine the CRITIC weight w_j via Eq. (14) and its subsequent normalizing expressions.
Phase 3: Evaluate and rank the alternatives
Step 8: Define the AI $\tilde{\xi}_{AI,j}$ and AAI $\tilde{\xi}_{AAI,j}$ solutions via Eqs. (15) and (16).
Step 9: Normalize the extended decision matrix to $\tilde{N} = [\tilde{n}_{ij}]_{(m+2)\times n}$ by applying the neutrosophic complement to cost criteria via Eq. (17).
Step 10: Compute the weighted normalized IVN matrix $\tilde{V} = [\tilde{v}_{ij}]_{(m+2)\times n}$ via Eq. (18).
Step 11: Deneutrosophicate to compute summation scores O_i, O_{ai}, O_{aai}, and calculate utility degrees K_i^- and K_i^+ via Eq. (19).
Step 12: Synthesize the comprehensive utility function $\Phi(K_i)$ via Eq. (20) and rank alternatives in descending order.

secondary-data numerical illustration concerning the siting of a centralized medical-waste disposal facility in Istanbul. As reported in the benchmark study, the original researchers conducted the preliminary geographical screening and consultations that identified four candidate sites: Pendik ($\mathcal{S}_1$), Arnavutköy ($\mathcal{S}_2$), Silivri ($\mathcal{S}_3$), and Şile ($\mathcal{S}_4$) [54]. The present study adopts these evaluations as a secondary-data case to demonstrate the applicability of the proposed framework.

As shown in Figure 2, an extensive evaluation model with 19 criteria has been developed to effectively evaluate these alternatives. These criteria are grouped into five core spatial and sustainability categories. Social and community areas include *proximity to educational facilities* (C_1) [54], *proximity to residential zones* (C_2) [55], *proximity to recreational and historical sites* (C_3) [56], *municipal endorsement* (C_4) [57], *community outreach* (C_5) [58], and *civic awareness* (C_6) [54], demonstrating the need to safeguard the well-being of citizens and mitigate potential public resistance.

The economic and financial domain covers *transportation expenses* (C_7) [59], *site acquisition cost* (C_8) [60], and *power expenses* (C_9) [61], supporting assessment of direct capital investment and long-term operating expenses. The ecological and environmental domain includes *proximity to hydrological systems* (C_{10}) [54], *separation from farmlands* (C_{11}) [60], and *terrain characteristics* (C_{12}) [62] are integrated to assess potential secondary pollution threats and protect natural ecosystems. The infrastructural and logistical domain comprises *highway accessibility* (C_{13}) [63], *railway connectivity* (C_{14}) [64], and *distance to disposal sites* (C_{15}) [65] which refers specifically to existing municipal landfills for post-incineration ash disposal and addresses logistics, efficiency, and regional connectivity requirements for hazardous-goods transportation. Ultimately, the geological and disaster risk profile involves *seismic vulnerability* (C_{16}) [66], *landslide vulnerability* (C_{17}) [67], *proximity to power grids* (C_{18}) [68], and *inundation risk* (C_{19}) [69], reflecting requirements for structural robustness and resilience to extreme natural events. Together, these 19 criteria provide a systematic representation of spatial viability and hazard mitigation.

This case study is reproduced based on data and experimental settings reported in a previous study [54]. In the referenced work, the evaluation of alternatives was carried out by a group of domain experts, denoted as $\mathcal{E} = \{\mathcal{E}_1, \mathcal{E}_2, \mathcal{E}_3\}$, with backgrounds in urban planning, environmental science, and social impact analysis. These experts assessed the candidate sites under the defined criteria using linguistic terms. The expert judgments, linguistic assessments, and resulting decision matrices are directly adopted from the literature in this study. The linguistic evaluations are subsequently transformed into IVNNs according to the predefined scale.

These linguistic terms directly evaluate the overall suitability of the alternatives rather than their raw numerical quantities; therefore, all 19 criteria are uniformly operationalized as benefit criteria in the mathematical normalization process. In this numerical illustration, the alternatives are assessed based on the spatial screenings established in the benchmark dataset.

4.2. Implementation steps

This subsection determines the optimal site for MW disposal facilities by executing the steps of the proposed model across three sequential phases.

Phase 1 Transforming linguistic evaluations and aggregating data.

Step 1: Under each evaluation criterion C_j ($j = 1, 2, \ldots, 19$), three experts $\mathcal{E}_k$ ($k = 1, 2, 3$) assess the potential sites for MW disposal $\mathcal{S}_i$ ($i = 1, 2, 3, 4$). These evaluations form the initial linguistic decision matrix, which is partially presented in Table 2. Based on the linguistic scale given in Table 1, the individual linguistic evaluations are transformed into IVNNs.

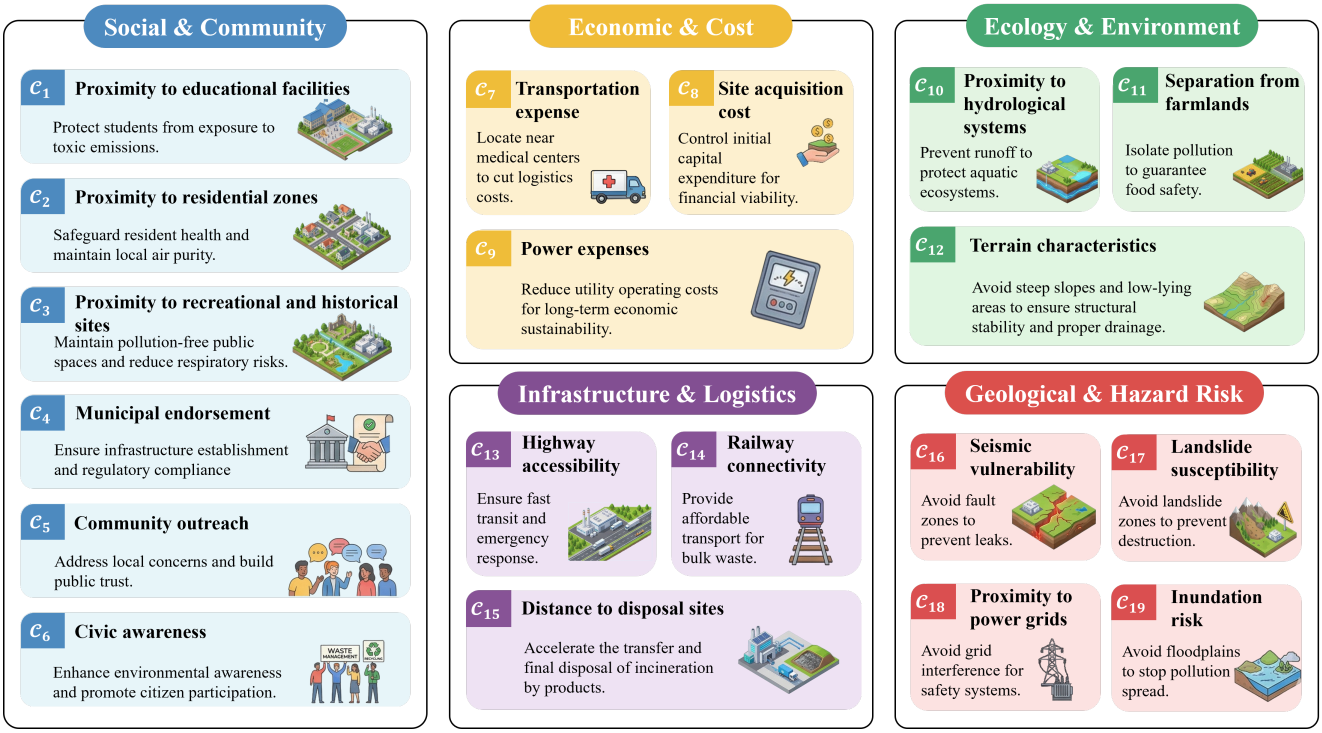

Figure 2: Comprehensive criteria system for optimal siting.

Table 1: Linguistic terms and IVNNs for evaluation.

Linguistic terms	Acronym	IVNNs
Extremely High	EH	$\langle[0.85, 0.95], [0.15, 0.25], [0.15, 0.25]\rangle$
Very High	VH	$\langle[0.75, 0.85], [0.25, 0.35], [0.25, 0.35]\rangle$
High	H	$\langle[0.65, 0.75], [0.45, 0.55], [0.35, 0.45]\rangle$
Medium High	MH	$\langle[0.60, 0.65], [0.55, 0.65], [0.45, 0.55]\rangle$
Medium	M	$\langle[0.55, 0.60], [0.65, 0.75], [0.45, 0.55]\rangle$
Medium Low	ML	$\langle[0.45, 0.55], [0.55, 0.65], [0.55, 0.65]\rangle$
Low	L	$\langle[0.35, 0.45], [0.45, 0.55], [0.65, 0.75]\rangle$
Very Low	VL	$\langle[0.25, 0.35], [0.35, 0.45], [0.75, 0.85]\rangle$
Extremely Low	EL	$\langle[0.15, 0.25], [0.15, 0.25], [0.85, 0.95]\rangle$

For the nine IVNNs adopted in this study, direct substitution into Eq. (6) gives the scores 0.950, 0.850, 0.755, 0.660, 0.575, 0.550, 0.500, 0.450, and 0.355 for EH through EL, respectively. Hence, the implemented scale satisfies the strict numerical order EH > VH > H > MH > M > ML > L > VL > EL.

Step 2: Let $\boldsymbol{\lambda} = \{\lambda_1, \ldots, \lambda_l\}$ be the expert weight vector ($\sum_{k=1}^{l} \lambda_k = 1$). Following the benchmark study [54], the baseline expert weight vector is adopted as $\boldsymbol{\lambda} = \{0.4, 0.3, 0.3\}$. In that study, all three experts had relevant experience in MW disposal facility projects. The study assigned weights of 0.4, 0.3, and 0.3 to Experts 1, 2, and 3, respectively. Because these weights enter the aggregation stage and may influence subsequent calculations, their effect is examined separately in the expert weight sensitivity analysis. Applying this vector, the individual assessments are aggregated using the INWAA operator to form the aggregated decision matrix $\Xi = [\tilde{\xi}_{ij}]_{m\times n}$, as presented in Table 3.

Phase 2 Determining criteria weights.

Step 3: The aggregated IVN matrix Ξ is converted into a crisp score matrix $S = [s_{ij}]_{4\times 19}$ utilizing the deneutrosophication mapping function defined in (6).

Step 4: To eliminate the influence of varying dimensions, the crisp score matrix S is normalized into a standard matrix $N = [n_{ij}]_{4\times 19}$ using Eq. (11).

Step 5: The standard deviation σ_j for each criterion is derived from the standard matrix according to Eq. (12) to quantify the contrast intensity.

Step 6: The linear correlation coefficient ρ_{jp} between criteria is computed based on Eq. (13) to measure the conflict between criteria.

Table 2: Linguistic decision matrix for alternatives.

Alternative	Expert	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	C_{18}	C_{19}
	$\mathcal{E}_1$	MH	VL	VL	VH	M	M	EH	H	EH	VL	VL	M	L	MH	L	L	EH	H	VH
$\mathcal{S}_1$	$\mathcal{E}_2$	H	VL	L	EH	M	H	VL	VH	VH	VL	VL	MH	L	H	L	L	VH	VH	VH
	$\mathcal{E}_3$	MH	VL	L	VH	MH	MH	L	EH	EH	L	VL	H	L	VH	VL	VL	EH	H	VH
	$\mathcal{E}_1$	ML	L	M	VL	VL	L	EL	L	VL	ML	ML	L	ML	L	MH	L	ML	L	ML
$\mathcal{S}_2$	$\mathcal{E}_2$	ML	ML	MH	L	L	L	EL	L	VL	ML	ML	ML	ML	L	H	ML	L	L	L
	$\mathcal{E}_3$	M	ML	H	VL	L	VL	L	L	VL	M	ML	ML	M	L	VH	L	ML	VL	L
	$\mathcal{E}_1$	L	M	L	M	M	ML	ML	L	L	MH	M	VL	M	L	M	M	ML	VL	ML
$\mathcal{S}_3$	$\mathcal{E}_2$	ML	MH	VL	M	MH	ML	ML	L	L	ML	ML	L	ML	VL	H	ML	M	VL	VL
	$\mathcal{E}_3$	L	H	L	MH	M	M	M	VL	EL	H	H	L	M	L	MH	M	MH	VL	VL
	$\mathcal{E}_1$	VL	MH	H	L	L	VL	MH	VL	EL	L	VL	L	VL	ML	L	H	H	VH	MH
$\mathcal{S}_4$	$\mathcal{E}_2$	L	MH	H	L	L	L	ML	L	VL	VL	L	VL	L	L	VL	VH	VH	VH	H
	$\mathcal{E}_3$	ML	H	M	VL	VL	EL	M	VL	EL	L	ML	L	L	M	L	VH	VH	VH	M

Step 7: Based on the calculated standard deviations and correlation coefficients, the information quantity Q_j and the final CRITIC weight w_j for each of the 19 criteria are reported in Table 4.

Phase 3 Ranking alternatives using the extended MARCOS method.

Step 8: For the extended MARCOS method, the AI and AAI reference points are first defined using Eq. (15) and (16) by identifying the maximum and minimum bounds of the aggregated evaluations.

Step 9: The extended decision matrix, which incorporates the alternatives along with the AI and AAI solutions, is normalized to $\tilde{N} = [\tilde{n}_{ij}]_{6\times19}$ via Eq. (17) to unify the criteria into a beneficial direction.

Step 10: By applying the data-driven criterion weights w_j, the weighted normalized IVN matrix $\tilde{V} = [\tilde{v}_{ij}]_{6\times19}$ is computed based on Eq. (18).

Step 11: The weighted IVNNs are deneutrosophicated with the same Eq. (6); the utility degrees K_i^+ and K_i^- are then determined from Eq. (19).

Step 12: Ultimately, the utility functions $f(K_i^+)$ and $f(K_i^-)$ are established, and the comprehensive utility function $\Phi(K_i)$ is derived using Eq. (20).

The detailed computational values generated from Phase 3 are tabulated in Table 5.

The final comprehensive utility values $\Phi(K_i)$ in Table 5 establish the ranking $\mathcal{S}_1 \succ \mathcal{S}_4 \succ \mathcal{S}_2 \succ \mathcal{S}_3$, with $\mathcal{S}_1$ in first place.

4.3. Sensitivity analysis

Five sensitivity checks were carried out. They cover changes in expert weights, equal criterion weights, changes in the four largest CRITIC weights, perturbations of the score matrix used by CRITIC, and simultaneous changes in all criterion weights. Monte Carlo simulation was used for the last two checks.

4.3.1. Sensitivity to expert weights

The baseline expert weights $\lambda = \{0.4, 0.3, 0.3\}$ are retained from the study [54], where the slightly larger weight assigned to Expert 1 reflects that expert's greater experience and participation in MW disposal facility projects abroad. To examine the influence of this baseline specification, four alternative settings were tested: the equal weighting case $\lambda = \{1/3, 1/3, 1/3\}$ and three cases in which one expert receives a weight of 0.8, namely $\{0.8, 0.1, 0.1\}$, $\{0.1, 0.8, 0.1\}$, and $\{0.1, 0.1, 0.8\}$. For each setting, the expert evaluations were aggregated again with the IN-WAA operator, followed by the CRITIC and MARCOS calculations.

All five expert weight settings give the same ranking, $\mathcal{S}_1 \succ \mathcal{S}_4 \succ \mathcal{S}_2 \succ \mathcal{S}_3$, as shown in Table 6. The tested changes in expert weights therefore do not alter the ranking. Expert inputs still affect the aggregated IVN matrix, so this result is limited to the weight settings considered here.

4.3.2. Equal criterion weights

The criterion weights were also set equally to $w_j = 1/19 \approx 0.0526$. Under this setting, the utility values were $\Phi(\mathcal{S}_1) = 0.7547$, $\Phi(\mathcal{S}_2) = 0.5351$, $\Phi(\mathcal{S}_3) = 0.5004$, and $\Phi(\mathcal{S}_4) = 0.6266$. The resulting ranking was $\mathcal{S}_1 \succ \mathcal{S}_4 \succ \mathcal{S}_2 \succ \mathcal{S}_3$, which is identical to the baseline ranking obtained with the CRITIC weights. The equal weight setting therefore changes the utility values but does not change the ordering of the four alternatives.

4.3.3. Individual criterion weight perturbation

The four largest CRITIC weights belong to C_3, C_{15}, C_2, and C_{13}, with baseline values of 0.0810, 0.0752, 0.0709, and 0.0696. Each of these weights was varied separately from -50% to $+50\%$ in steps of 10%. The other 18 weights were rescaled proportionally so that their sum remained one. Since the perturbation is applied after CRITIC has produced the weights, this test measures sensitivity to individual weight changes and does not assess the stability of the CRITIC correlation estimates.

Table 3: The aggregated IVN decision matrix.

Alternative	C_1	C_2	C_3	C_4	C_5
$\mathcal{S}_1$	$\langle[0.6157, 0.6836], [0.5179, 0.6182], [0.4173, 0.5179]\rangle$	$\langle[0.2500, 0.3500], [0.3500, 0.4500], [0.7500, 0.8500]\rangle$	$\langle[0.3117, 0.4120], [0.4070, 0.5076], [0.6883, 0.7885]\rangle$	$\langle[0.7855, 0.8921], [0.2145, 0.3164], [0.2145, 0.3164]\rangle$	$\langle[0.5656, 0.6157], [0.6182, 0.7185], [0.4500, 0.5500]\rangle$
$\mathcal{S}_2$	$\langle[0.4821, 0.5656], [0.5783, 0.6785], [0.5179, 0.6182]\rangle$	$\langle[0.4120, 0.5124], [0.5076, 0.6080], [0.5880, 0.6883]\rangle$	$\langle[0.5972, 0.6662], [0.5537, 0.6546], [0.4173, 0.5179]\rangle$	$\langle[0.2815, 0.3818], [0.3774, 0.4779], [0.7185, 0.8187]\rangle$	$\langle[0.3117, 0.4120], [0.4070, 0.5076], [0.6883, 0.7885]\rangle$
$\mathcal{S}_3$	$\langle[0.3818, 0.4821], [0.4779, 0.5783], [0.6182, 0.7185]\rangle$	$\langle[0.5972, 0.6662], [0.5537, 0.6546], [0.4173, 0.5179]\rangle$	$\langle[0.3215, 0.4217], [0.4173, 0.5179], [0.6785, 0.7787]\rangle$	$\langle[0.5656, 0.6157], [0.6182, 0.7185], [0.4500, 0.5500]\rangle$	$\langle[0.5656, 0.6157], [0.6182, 0.7185], [0.4500, 0.5500]\rangle$
$\mathcal{S}_4$	$\langle[0.3454, 0.4463], [0.4322, 0.5337], [0.6546, 0.7554]\rangle$	$\langle[0.6157, 0.6836], [0.5179, 0.6182], [0.4173, 0.5179]\rangle$	$\langle[0.6226, 0.7121], [0.5025, 0.6036], [0.3774, 0.4779]\rangle$	$\langle[0.3215, 0.4217], [0.4173, 0.5179], [0.6785, 0.7787]\rangle$	$\langle[0.3215, 0.4217], [0.4173, 0.5179], [0.6785, 0.7787]\rangle$

Alternative	C_6	C_7	C_8	C_9	C_{10}
$\mathcal{S}_1$	$\langle[0.5972, 0.6662], [0.5537, 0.6546], [0.4173, 0.5179]\rangle$	$\langle[0.6226, 0.7784], [0.2689, 0.3778], [0.3774, 0.5018]\rangle$	$\langle[0.7546, 0.8677], [0.2713, 0.3791], [0.2454, 0.3499]\rangle$	$\langle[0.8252, 0.9305], [0.1748, 0.2766], [0.1748, 0.2766]\rangle$	$\langle[0.2815, 0.3818], [0.3774, 0.4779], [0.7185, 0.8187]\rangle$
$\mathcal{S}_2$	$\langle[0.3215, 0.4217], [0.4173, 0.5179], [0.6785, 0.7787]\rangle$	$\langle[0.2157, 0.3166], [0.2086, 0.3167], [0.7843, 0.8850]\rangle$	$\langle[0.3500, 0.4500], [0.4500, 0.5500], [0.6500, 0.7500]\rangle$	$\langle[0.2500, 0.3500], [0.3500, 0.4500], [0.7500, 0.8500]\rangle$	$\langle[0.4821, 0.5656], [0.5783, 0.6785], [0.5179, 0.6182]\rangle$
$\mathcal{S}_3$	$\langle[0.4821, 0.5656], [0.5783, 0.6785], [0.5179, 0.6182]\rangle$	$\langle[0.4821, 0.5656], [0.5783, 0.6785], [0.5179, 0.6182]\rangle$	$\langle[0.3215, 0.4217], [0.4173, 0.5179], [0.6785, 0.7787]\rangle$	$\langle[0.2955, 0.3964], [0.3237, 0.4341], [0.7045, 0.8051]\rangle$	$\langle[0.5772, 0.6588], [0.5179, 0.6182], [0.4432, 0.5445]\rangle$
$\mathcal{S}_4$	$\langle[0.2540, 0.3547], [0.2927, 0.4007], [0.7460, 0.8465]\rangle$	$\langle[0.5441, 0.6072], [0.5783, 0.6785], [0.4779, 0.5783]\rangle$	$\langle[0.2815, 0.3818], [0.3774, 0.4779], [0.7185, 0.8187]\rangle$	$\langle[0.1813, 0.2815], [0.1934, 0.2982], [0.8187, 0.9188]\rangle$	$\langle[0.3215, 0.4217], [0.4173, 0.5179], [0.6785, 0.7787]\rangle$

Alternative	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
$\mathcal{S}_1$	$\langle[0.2500, 0.3500], [0.3500, 0.4500], [0.7500, 0.8500]\rangle$	$\langle[0.5972, 0.6662], [0.5537, 0.6546], [0.4173, 0.5179]\rangle$	$\langle[0.3500, 0.4500], [0.4500, 0.5500], [0.6500, 0.7500]\rangle$	$\langle[0.6662, 0.7546], [0.4088, 0.5134], [0.3499, 0.4522]\rangle$	$\langle[0.3215, 0.4217], [0.4173, 0.5179], [0.6785, 0.7787]\rangle$
$\mathcal{S}_2$	$\langle[0.4500, 0.5500], [0.5500, 0.6500], [0.5500, 0.6500]\rangle$	$\langle[0.4120, 0.5124], [0.5076, 0.6080], [0.5880, 0.6883]\rangle$	$\langle[0.4821, 0.5656], [0.5783, 0.6785], [0.5179, 0.6182]\rangle$	$\langle[0.3500, 0.4500], [0.4500, 0.5500], [0.6500, 0.7500]\rangle$	$\langle[0.6662, 0.7546], [0.4088, 0.5134], [0.3499, 0.4522]\rangle$
$\mathcal{S}_3$	$\langle[0.5568, 0.6401], [0.5537, 0.6546], [0.4432, 0.5445]\rangle$	$\langle[0.3117, 0.4120], [0.4070, 0.5076], [0.6883, 0.7885]\rangle$	$\langle[0.5221, 0.5856], [0.6182, 0.7185], [0.4779, 0.5783]\rangle$	$\langle[0.3215, 0.4217], [0.4173, 0.5179], [0.6785, 0.7787]\rangle$	$\langle[0.5972, 0.6662], [0.5537, 0.6546], [0.4173, 0.5179]\rangle$
$\mathcal{S}_4$	$\langle[0.3454, 0.4463], [0.4322, 0.5337], [0.6546, 0.7554]\rangle$	$\langle[0.3215, 0.4217], [0.4173, 0.5179], [0.6785, 0.7787]\rangle$	$\langle[0.3117, 0.4120], [0.4070, 0.5076], [0.6883, 0.7885]\rangle$	$\langle[0.4555, 0.5387], [0.5445, 0.6453], [0.5445, 0.6453]\rangle$	$\langle[0.3215, 0.4217], [0.4173, 0.5179], [0.6785, 0.7787]\rangle$

Alternative	C_{16}	C_{17}	C_{18}	C_{19}
$\mathcal{S}_1$	$\langle[0.3215, 0.4217], [0.4173, 0.5179], [0.6785, 0.7787]\rangle$	$\langle[0.8252, 0.9305], [0.1748, 0.2766], [0.1748, 0.2766]\rangle$	$\langle[0.6836, 0.7855], [0.3773, 0.4803], [0.3164, 0.4173]\rangle$	$\langle[0.7500, 0.8500], [0.2500, 0.3500], [0.2500, 0.3500]\rangle$
$\mathcal{S}_2$	$\langle[0.3818, 0.4821], [0.4779, 0.5783], [0.6182, 0.7185]\rangle$	$\langle[0.4217, 0.5221], [0.5179, 0.6182], [0.5783, 0.6785]\rangle$	$\langle[0.3215, 0.4217], [0.4173, 0.5179], [0.6785, 0.7787]\rangle$	$\langle[0.3920, 0.4924], [0.4876, 0.5880], [0.6080, 0.7083]\rangle$
$\mathcal{S}_3$	$\langle[0.5221, 0.5856], [0.6182, 0.7185], [0.4779, 0.5783]\rangle$	$\langle[0.5293, 0.5972], [0.5783, 0.6785], [0.4876, 0.5880]\rangle$	$\langle[0.2500, 0.3500], [0.3500, 0.4500], [0.7500, 0.8500]\rangle$	$\langle[0.3375, 0.4389], [0.4194, 0.5213], [0.6625, 0.7635]\rangle$
$\mathcal{S}_4$	$\langle[0.7140, 0.8160], [0.3163, 0.4194], [0.2860, 0.3870]\rangle$	$\langle[0.7140, 0.8160], [0.3163, 0.4194], [0.2860, 0.3870]\rangle$	$\langle[0.7500, 0.8500], [0.2500, 0.3500], [0.2500, 0.3500]\rangle$	$\langle[0.6019, 0.6707], [0.5445, 0.6453], [0.4173, 0.5179]\rangle$

All 40 nonzero one-at-a-time perturbation cases, together with the baseline setting, retained the ranking $\mathcal{S}_1 \succ \mathcal{S}_4 \succ \mathcal{S}_2 \succ \mathcal{S}_3$. The retention rate is therefore 100%, and no crossover occurs among the alternatives over the tested range. This result supports local ranking stability for the four individual weight perturbations, but it does not show that the CRITIC correlation estimates are invariant.

Table 4: Standard deviation, information quantity, and CRITIC criterion weights.

Criteria	σ_j	Q_j	w_j	Criteria	σ_j	Q_j	w_j
C_1	0.4523	6.1656	0.0407	C_{11}	0.4269	9.5973	0.0633
C_2	0.4712	10.7374	0.0709	C_{12}	0.4664	6.3742	0.0421
C_3	0.5182	12.2735	0.0810	C_{13}	0.4923	10.5531	0.0696
C_4	0.4607	5.8468	0.0386	C_{14}	0.4649	6.1110	0.0403
C_5	0.5660	7.9860	0.0527	C_{15}	0.4953	11.3918	0.0752
C_6	0.4379	5.7609	0.0380	C_{16}	0.4553	9.8352	0.0649
C_7	0.4126	5.4991	0.0363	C_{17}	0.4747	6.7341	0.0444
C_8	0.4790	6.2429	0.0412	C_{18}	0.5161	8.3273	0.0550
C_9	0.4596	5.9597	0.0393	C_{19}	0.4603	6.3397	0.0418
C_{10}	0.4523	9.7966	0.0647				

Table 5: Final results of alternatives using MARCOS.

Alternative	K^+	K^-	$f(K^+)$	$f(K^-)$	$\Phi(K_i)$
$\mathcal{S}_1$	0.8596	1.7170	0.6664	0.3336	0.7366
$\mathcal{S}_2$	0.6371	1.2725	0.6664	0.3336	0.5459
$\mathcal{S}_3$	0.5999	1.1982	0.6664	0.3336	0.5140
$\mathcal{S}_4$	0.7533	1.5047	0.6664	0.3336	0.6455

Table 6: Sensitivity to different expert weight settings.

$\{\lambda_1, \lambda_2, \lambda_3\}$	$\Phi(\mathcal{S}_1)$	$\Phi(\mathcal{S}_2)$	$\Phi(\mathcal{S}_3)$	$\Phi(\mathcal{S}_4)$	Ranking
$\{0.4, 0.3, 0.3\}$	0.7366	0.5459	0.5140	0.6455	$\mathcal{S}_1 \succ \mathcal{S}_4 \succ \mathcal{S}_2 \succ \mathcal{S}_3$
$\{1/3, 1/3, 1/3\}$	0.7360	0.5457	0.5176	0.6447	$\mathcal{S}_1 \succ \mathcal{S}_4 \succ \mathcal{S}_2 \succ \mathcal{S}_3$
$\{0.8, 0.1, 0.1\}$	0.7381	0.5470	0.4902	0.6472	$\mathcal{S}_1 \succ \mathcal{S}_4 \succ \mathcal{S}_2 \succ \mathcal{S}_3$
$\{0.1, 0.8, 0.1\}$	0.7308	0.5417	0.5194	0.6470	$\mathcal{S}_1 \succ \mathcal{S}_4 \succ \mathcal{S}_2 \succ \mathcal{S}_3$
$\{0.1, 0.1, 0.8\}$	0.7390	0.5371	0.5262	0.6230	$\mathcal{S}_1 \succ \mathcal{S}_4 \succ \mathcal{S}_2 \succ \mathcal{S}_3$

4.3.4. CRITIC sensitivity to decision data perturbation

CRITIC estimates the correlation structure from only four alternatives in this case. A Monte Carlo test was therefore added at the data level. Random changes were introduced directly into the deneutrosophicated score matrix before CRITIC normalization and weight calculation.

$$s_{ij}^{(b)} = s_{ij} + u_{ij}^{(b)}\delta\left(\max_i s_{ij} - \min_i s_{ij}\right), \tag{22}$$

In Eq. (22), $u_{ij}^{(b)} \sim U(-1, 1)$, b indexes the Monte Carlo replication, and δ controls the perturbation size. The tested levels are ±5%, ±10%, and ±20%, with 10,000 replications at each level. In every replication, the perturbed matrix is normalized again, and the standard deviations, Pearson correlations, information quantities, and CRITIC weights are recalculated. These weights are then used in MARCOS, while the aggregated IVN evaluation matrix is kept unchanged. In this way, the test focuses on changes that enter through the CRITIC estimation step.

Table 7 presents the Pearson correlation matrix, which was derived using the deneutrosophication function outlined in Eq. (6). With only four alternatives, these coefficients are used as descriptive inputs to CRITIC and are not treated as inferential estimates from a large sample.

At the three tested perturbation levels of ±5%, ±10%, and ±20%, 10,000 Monte Carlo replications were conducted at each level. Across all 30,000 simulations, $\mathcal{S}_1$ remained the top-ranked alternative, and the complete ranking $\mathcal{S}_1 \succ \mathcal{S}_4 \succ \mathcal{S}_2 \succ \mathcal{S}_3$ was preserved in every case. The mean Spearman rank correlation coefficient with the baseline ranking was 1.0000 at all three perturbation levels. No ranking reversal was observed within the tested range.

The CRITIC weights do vary even though the final ranking does not. Table 8 reports the criteria that have a nonzero chance of entering the four largest weights at the strongest tested perturbation, ±20%. The interval limits are the empirical 2.5th and 97.5th percentiles.

At ±20%, the probabilities that C_3, C_{15}, C_2, and C_{13} remain among the four largest weights are 97.20%, 87.45%, 88.64%, and 62.25%, respectively. C_{10}, C_{11}, and C_{16} enter the four largest weights in some replications. The exact order of the CRITIC weights is therefore sensitive to changes in the input data, which is an important limitation when the correlations are calculated from four alternatives.

Table 7: Pearson correlation matrix of the normalized criteria.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
C_1	1.0000	-0.9320	-0.5500	0.8765	0.4886	0.8527	0.5652	0.9743	0.9705	-0.5137
C_2	-0.9320	1.0000	0.3771	-0.6575	-0.2576	-0.6878	-0.2325	-0.8270	-0.8206	0.4315
C_3	-0.5500	0.3771	1.0000	-0.7928	-0.9811	-0.9013	-0.5058	-0.5994	-0.6705	-0.3020
C_4	0.8765	-0.6575	-0.7928	1.0000	0.8017	0.9616	0.8240	0.9470	0.9656	-0.3414
C_5	0.4886	-0.2576	-0.9811	0.8017	1.0000	0.8711	0.6204	0.5798	0.6462	0.2551
C_6	0.8527	-0.6878	-0.9013	0.9616	0.8711	1.0000	0.6588	0.8851	0.9248	-0.1109
C_7	0.5652	-0.2325	-0.5058	0.8240	0.6204	0.6588	1.0000	0.7363	0.7268	-0.5196
C_8	0.9743	-0.8270	-0.5994	0.9470	0.5798	0.8851	0.7363	1.0000	0.9955	-0.5525
C_9	0.9705	-0.8206	-0.6705	0.9656	0.6462	0.9248	0.7268	0.9955	1.0000	-0.4718
C_{10}	-0.5137	0.4315	-0.3020	-0.3414	0.2551	-0.1109	-0.5196	-0.5525	-0.4718	1.0000
C_{11}	-0.6490	0.5542	-0.1492	-0.4838	0.1156	-0.2722	-0.5891	-0.6837	-0.6121	0.9858
C_{12}	0.9944	-0.9203	-0.4758	0.8590	0.4247	0.8082	0.5917	0.9756	0.9622	-0.6015
C_{13}	-0.2331	0.0327	-0.3001	-0.2659	0.1720	0.0081	-0.6658	-0.3634	-0.2886	0.8887
C_{14}	0.9051	-0.7192	-0.4387	0.8951	0.4588	0.7649	0.8268	0.9654	0.9411	-0.7225
C_{15}	-0.3044	-0.0067	0.0820	-0.5180	-0.2351	-0.2737	-0.8975	-0.4896	-0.4463	0.6979
C_{16}	-0.6769	0.7837	0.6652	-0.5261	-0.5112	-0.7129	0.0476	-0.5489	-0.5998	-0.2189
C_{17}	0.5510	-0.2776	-0.1565	0.6669	0.2692	0.4368	0.9160	0.6965	0.6504	-0.8107
C_{18}	0.2946	-0.0819	0.2321	0.3364	-0.1063	0.0658	0.7138	0.4274	0.3558	-0.8940
C_{19}	0.7555	-0.5446	-0.2175	0.7605	0.2789	0.5647	0.8549	0.8475	0.8025	-0.8571

	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	C_{18}	C_{19}
C_1	-0.6490	0.9944	-0.2331	0.9051	-0.3044	-0.6769	0.5510	0.2946	0.7555
C_2	0.5542	-0.9203	0.0327	-0.7192	-0.0067	0.7837	-0.2776	-0.0819	-0.5446
C_3	-0.1492	-0.4758	-0.3001	-0.4387	0.0820	0.6652	-0.1565	0.2321	-0.2175
C_4	-0.4838	0.8590	-0.2659	0.8951	-0.5180	-0.5261	0.6669	0.3364	0.7605
C_5	0.1156	0.4247	0.1720	0.4588	-0.2351	-0.5112	0.2692	-0.1063	0.2789
C_6	-0.2722	0.8082	0.0081	0.7649	-0.2737	-0.7129	0.4368	0.0658	0.5647
C_7	-0.5891	0.5917	-0.6658	0.8268	-0.8975	0.0476	0.9160	0.7138	0.8549
C_8	-0.6837	0.9756	-0.3634	0.9654	-0.4896	-0.5489	0.6965	0.4274	0.8475
C_9	-0.6121	0.9622	-0.2886	0.9411	-0.4463	-0.5998	0.6504	0.3558	0.8025
C_{10}	0.9858	-0.6015	0.8887	-0.7225	0.6979	-0.2189	-0.8107	-0.8940	-0.8571
C_{11}	1.0000	-0.7258	0.8420	-0.8231	0.6950	-0.0708	-0.8391	-0.8593	-0.9148
C_{12}	-0.7258	1.0000	-0.3272	0.9323	-0.3706	-0.6027	0.6139	0.3852	0.8097
C_{13}	0.8420	-0.3272	1.0000	-0.5937	0.9059	-0.5567	-0.8925	-0.9973	-0.8024
C_{14}	-0.8231	0.9323	-0.5937	1.0000	-0.6797	-0.3166	0.8531	0.6484	0.9566
C_{15}	0.6950	-0.3706	0.9059	-0.6797	1.0000	-0.4428	-0.9583	-0.9249	-0.8326
C_{16}	-0.0708	-0.6027	-0.5567	-0.3166	-0.4428	1.0000	0.2166	0.5038	-0.0329
C_{17}	-0.8391	0.6139	-0.8925	0.8531	-0.9583	0.2166	1.0000	0.9231	0.9562
C_{18}	-0.8593	0.3852	-0.9973	0.6484	-0.9249	0.5038	0.9231	1.0000	0.8420
C_{19}	-0.9148	0.8097	-0.8024	0.9566	-0.8326	-0.0329	0.9562	0.8420	1.0000

Despite these changes in the CRITIC weights, the alternative ranking remained unchanged in all tested data perturbations.

4.3.5. *Simultaneous criterion weight perturbation*

A second Monte Carlo test changes all 19 criterion weights at the same time. For each replication, the weights are calculated as

$$w_j^{(b)} = \frac{w_j\left(1+\varepsilon_j^{(b)}\right)}{\sum_{k=1}^{19} w_k\left(1+\varepsilon_k^{(b)}\right)}, \qquad \varepsilon_j^{(b)} \sim U(-\delta,\delta). \tag{23}$$

Eq. (23) keeps the perturbed weights nonnegative and normalizes their sum to one. Ten levels from ±5% to ±50% were tested in steps of five percentage points, with 10,000 replications at each level. Across all 100,000 simulations, $\mathcal{S}_1$ remained the top-ranked alternative and the complete ranking $\mathcal{S}_1 \succ \mathcal{S}_4 \succ \mathcal{S}_2 \succ \mathcal{S}_3$ was preserved. No ranking reversal was

Table 8: CRITIC weight variation at the ±20% data perturbation level.

Criterion	Baseline weight	Mean weight	SD	95% empirical interval	Top four inclusion rate
C_3	0.0810	0.0782	0.0058	[0.0673, 0.0897]	97.20%
C_{15}	0.0752	0.0725	0.0046	[0.0633, 0.0819]	87.45%
C_2	0.0709	0.0710	0.0036	[0.0642, 0.0783]	88.64%
C_{13}	0.0696	0.0697	0.0065	[0.0581, 0.0825]	62.25%
C_{10}	0.0647	0.0649	0.0036	[0.0583, 0.0726]	22.11%
C_{11}	0.0633	0.0652	0.0036	[0.0595, 0.0733]	23.16%
C_{16}	0.0649	0.0648	0.0031	[0.0582, 0.0707]	19.18%
C_{17}	0.0444	0.0458	0.0046	[0.0384, 0.0558]	0.01%

observed, so the empirical reversal threshold was not reached within the tested range. This simulation result does not prove that every possible weight combination within or beyond this range will preserve the ranking.

The sensitivity results distinguish changes in criterion weights from changes in the final ranking. The CRITIC weights vary when the underlying score matrix is perturbed, and the four largest weights are not fixed in every simulation. Even so, the alternative ranking does not change in the tests reported here. The baseline ranking is retained for all expert weight settings, the equal criterion weight case, all 40 individual weight perturbations, all 30,000 CRITIC data perturbation simulations, and all 100,000 simultaneous weight simulations. These results support ranking stability within the tested settings and ranges, but they do not establish global robustness.

4.4. Comparison with other models

This section compares the ranking outcomes of the proposed model with IVN-TOPSIS [39], IVN-MAIRCA [53], IVN-EDAS [54], and IVN-VIKOR [70]. These methods provide complementary IVN benchmark frameworks with different weighting and ranking mechanisms. Accordingly, the comparison focuses on the overall performance differences among integrated decision frameworks.

4.4.1. IVN-TOPSIS

The IVN-TOPSIS model is used to evaluate and optimize the location of MW disposal facilities. Initially, the experts' linguistic ratings are transformed into IVNNs, and the aggregate decision matrix is constructed. The weighted normalized decision matrix is then constructed, after which the positive ideal solution (PIS) and the negative ideal solution (NIS) are established according to the characteristics of the criteria. The weighted Euclidean distance between each scheme and the ideal solution is calculated.

The results for the distances to the PIS (D^+) are 1.3106, 2.5075, 2.4251, and 2.2356, while the distances to the NIS (D^-) are 2.6306, 1.2391, 1.5304, and 1.7443 for alternatives $\mathcal{S}_1$ through $\mathcal{S}_4$. Consequently, the closeness coefficients (CC_i) are determined as $CC_1 = 0.6675$, $CC_2 = 0.3307$, $CC_3 = 0.3869$, and $CC_4 = 0.4383$. This yields the final ranking order of $\mathcal{S}_1 \succ \mathcal{S}_4 \succ \mathcal{S}_3 \succ \mathcal{S}_2$.

4.4.2. IVN-MAIRCA

The IVN-MAIRCA model is used to evaluate and select the location of MW disposal facilities. To begin with, the aggregated decision matrix is deneutrosophicated, and the criterion weights are derived using the Shannon entropy measure. After normalizing the decision matrix, the theoretical and the real rating matrices are constructed to determine the expected and empirical evaluations for each alternative. Subsequently, the total gap matrix is computed by subtracting the theoretical ratings from the real ratings. The criterion functions Q_i for each alternative, representing the summation of the gap values across all criteria, are computed as follows: $Q_1 = 0.0611$, $Q_2 = 0.2030$, $Q_3 = 0.1869$, and $Q_4 = 0.1581$. Based on the MAIRCA evaluation rule, where a smaller total gap value indicates closer proximity to the ideal solution, the final ranking order of the alternatives is determined to be $\mathcal{S}_1 \succ \mathcal{S}_4 \succ \mathcal{S}_3 \succ \mathcal{S}_2$.

4.4.3. IVN-EDAS

The IVN-EDAS model is employed to evaluate and select the optimal site for MW disposal facilities. The decision matrix is processed using the predefined linguistic terms, and the derived attribute and expert weights are applied accordingly. Following the calculation of the average solutions for each criterion, the deneutrosophicated weighted sums of positive distances $K(SP_i)$ and negative distances $K(NP_i)$ from the average solution for each alternative are calculated as follows: $K(SP_1) = 0.6345$, $K(NP_1) = 0.3717$; $K(SP_2) = 0.5451$, $K(NP_2) = 0.4544$; $K(SP_3) = 0.5294$, $K(NP_3) = 0.4700$; and $K(SP_4) = 0.5824$, $K(NP_4) = 0.4168$. Finally, the deneutrosophicated appraisal scores (AS_i) are determined to be $AS_1 = 0.8081$, $AS_2 = 0.7569$, $AS_3 = 0.7417$, and $AS_4 = 0.7878$. Based on these scores, the final ranking order of the alternatives is $\mathcal{S}_1 \succ \mathcal{S}_4 \succ \mathcal{S}_2 \succ \mathcal{S}_3$.

4.4.4. IVN-VIKOR

The IVN-VIKOR model is employed to evaluate and select the optimal site for MW disposal facilities. Initially, the expert weights are determined, and the linguistic evaluations provided by the decision-makers are aggregated into an IVN decision matrix utilizing the INWAA operator. Then, the criterion weights are established. Subsequently, the positive and negative ideal solutions are defined, and the normalized Hamming distances between each alternative and these ideal solutions are

Table 9: Comparison of evaluation results with existing models.

Model	$\mathcal{S}_1$	$\mathcal{S}_2$	$\mathcal{S}_3$	$\mathcal{S}_4$	Ranking
Proposed model	0.7366	0.5459	0.5140	0.6455	$\mathcal{S}_1 > \mathcal{S}_4 > \mathcal{S}_2 > \mathcal{S}_3$
IVN-TOPSIS	0.6675	0.3307	0.3869	0.4383	$\mathcal{S}_1 > \mathcal{S}_4 > \mathcal{S}_3 > \mathcal{S}_2$
IVN-MAIRCA	0.0611	0.2030	0.1869	0.1581	$\mathcal{S}_1 > \mathcal{S}_4 > \mathcal{S}_3 > \mathcal{S}_2$
IVN-EDAS	0.8081	0.7569	0.7417	0.7878	$\mathcal{S}_1 > \mathcal{S}_4 > \mathcal{S}_2 > \mathcal{S}_3$
IVN-VIKOR	0.0000	0.7120	0.9609	0.8626	$\mathcal{S}_1 > \mathcal{S}_2 > \mathcal{S}_4 > \mathcal{S}_3$

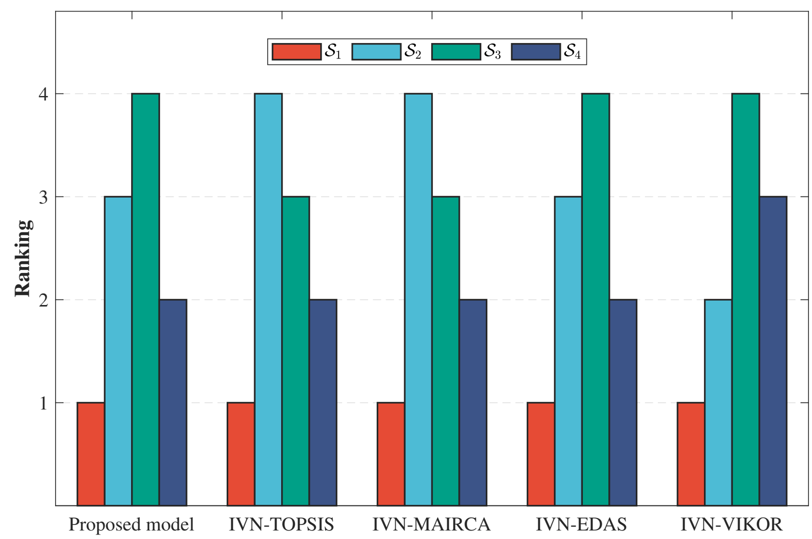

Figure 3: Ranking order of sites for MW disposal facilities with different models. A lower rank number indicates superior performance.

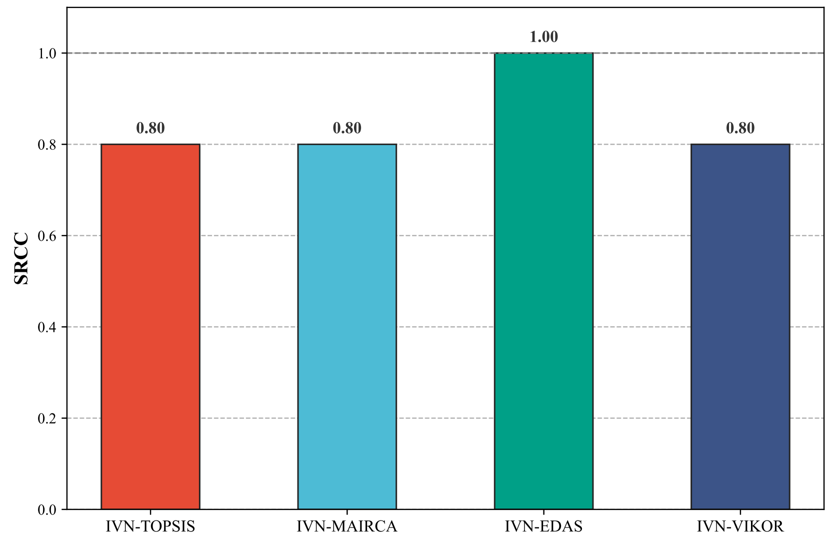

Figure 4: SRCC comparison of existing models with the proposed framework.

computed. Based on these distances and attribute weights, the group utility measures ($\mathcal{S}_i$) and the individual regret measures (R_i) are calculated.

The results are obtained as $\mathcal{S}_1 = 0.3267$, $\mathcal{S}_2 = 0.6452$,

$\mathcal{S}_3 = 0.6203$, and $\mathcal{S}_4 = 0.5772$; while the regret measures are $R_1 = 0.0520$, $R_2 = 0.0607$, $R_3 = 0.0726$, and $R_4 = 0.0713$, respectively. Finally, by integrating group utility and the individual regret value, the decision-making mechanism coefficient $v = 0.5$ is used to balance the majority consensus and the minimum individual veto power, and a compromise index (Q_i) is obtained. The final indices are determined to be $Q_1 = 0.0000$, $Q_2 = 0.7120$, $Q_3 = 0.9609$, and $Q_4 = 0.8626$. According to the VIKOR ranking principle, the final ranking order of alternatives is $\mathcal{S}_1 \succ \mathcal{S}_2 \succ \mathcal{S}_4 \succ \mathcal{S}_3$.

4.4.5. Comparative analysis

The methodological scope of this comparison is explicitly limited to an integrated-framework comparison rather than a controlled ranking-algorithm experiment. The same initial aggregated IVN decision matrix is supplied to the benchmark frameworks, but each method retains its own weighting procedure and ranking mechanism, such as the Shannon entropy weighting used in the MAIRCA implementation. Therefore, ranking differences should be interpreted in the context of the complete decision frameworks.

Table 9 and Figure 3 show that all five frameworks rank $\mathcal{S}_1$ first. The proposed model and IVN-EDAS produce the same complete ordering, $\mathcal{S}_1 \succ \mathcal{S}_4 \succ \mathcal{S}_2 \succ \mathcal{S}_3$, whereas IVN-TOPSIS and IVN-MAIRCA interchange the positions of $\mathcal{S}_2$ and $\mathcal{S}_3$, and IVN-VIKOR produces a different ordering among the remaining three alternatives. Agreement is strongest for the top-ranked site, while the order of less optimal alternatives varies by method. Since the frameworks employ different weighting and ranking processes, these variations cannot be attributed to any single algorithmic component.

Spearman rank correlation coefficient (SRCC) is used only as a descriptive measure of ranking alignment. With four alternatives, the coefficient takes highly discrete values and should not be interpreted as statistical validation. Based on the proposed ranking, SRCC values are 0.8000 with IVN-TOPSIS, 0.8000 with IVN-MAIRCA, 1.0000 with IVN-EDAS, and 0.8000 with IVN-VIKOR. These values indicate substantial ordinal agreement across the comparable frameworks while confirming that complete rank equivalence occurs only with IVN-EDAS in the present comparison. The corresponding SRCC values are shown in Figure 4.

Based on the comparative analysis and the calculation process described in the case study, several methodological characteristics of the proposed model can be summarized:

The framework uses CRITIC to derive criterion weights from both score dispersion and inter-criterion correlation conflict. This differs from entropy-based weighting procedures that use a different information structure. In the present study, this difference is treated as a methodological distinction rather than evidence that one weighting scheme is universally superior.

The extended MARCOS stage evaluates alternatives relative to both AI and AAI reference points through the comprehensive utility function $\Phi(K_i)$. This dual-reference construction differs from the distance- or compromise-based mechanisms used by the benchmark methods. The comparison results are used to describe these methodological differences and their resulting rankings, without claiming that the MARCOS mechanism is intrinsically more stable or more accurate in the absence of a controlled comparison.

Because the comparable frameworks vary simultaneously in their weighting procedures and ranking mechanisms, the observed differences cannot be decomposed into separate weighting-method and ranking-method effects in the present experiment. The comparison is therefore interpreted only at the integrated-framework level, and no claim is made that the suboptimal ranking differences are caused by, or demonstrate the superiority of, a particular ranking algorithm.

5. Conclusion

This study develops an IVN-CRITIC-MARCOS decision-support framework for medical-waste disposal facility siting under uncertain expert evaluations. IVNSs are used to represent interval-valued truth, indeterminacy, and falsity information, while CRITIC derives data-driven criterion weights from dispersion and inter-criterion conflict, and MARCOS ranks the alternatives relative to AI and AAI reference solutions. The CRITIC procedure avoids direct subjective assignment of criterion weights, but its outputs remain dependent on the elicited expert matrix and the adopted deneutrosophication function. In the secondary-data Istanbul illustration, Pendik ($\mathcal{S}_1$) is identified as the highest-ranked alternative. All four studies also rank $\mathcal{S}_1$ first, while the ordering of the remaining alternatives varies across methods; IVN-EDAS is the only study that produces the same complete ranking as the proposed model. Because the comparable frameworks retain different weighting and ranking mechanisms, these differences are interpreted at the integrated-framework level rather than being attributed to the ranking algorithms alone. The sensitivity results further indicate that the final ranking remains unchanged under the perturbation scenarios examined in this study, although further validation under broader scenarios is required.

Several limitations of the present study should be acknowledged:

The evaluation process involves three experts, which may not fully capture the diverse perspectives of stakeholders in controversial public infrastructure projects. Future applications may therefore employ larger expert panels together with group consensus procedures.

The criterion weights are derived using the CRITIC method rather than being assigned directly by experts. However, this does not eliminate subjectivity because the CRITIC inputs originate from the elicited expert matrix and depend on the adopted deneutrosophication function. Future research may examine hybrid weighting designs that combine explicit expert preferences with data-driven weighting information.

The application of the CRITIC method to only four alternatives remains an important methodological limitation because the standard deviations and pairwise correlations are estimated from only four observations. To further assess this limitation, the Monte Carlo analysis perturbs the CRITIC input matrix and recalculates the correlations and weights in each replication. Although the final ranking remained unchanged across all tested simulations, the observed variation in the criterion weights indicates that the CRITIC estimates obtained from such a small set of alternatives should still be interpreted with caution.

The empirical analysis is limited to the spatial context of Istanbul. Future research should examine the applicability of the proposed IVN-CRITIC-MARCOS framework in other high-risk environmental engineering settings, such as nuclear-waste repository siting or chemical-recovery facility selection under different geographical and regulatory conditions.

The adopted linguistic scale contains asymmetric interval specifications. Under the selected deneutrosophication function, the nine terms used in this study satisfy the verified strict score order EH > VH > H > MH > M > ML > L > VL > EL. This verification is specific to the adopted scale and should not be interpreted as a global monotonicity guarantee for every admissible IVNN.

Data availability

The secondary input data used in the numerical illustration were adopted from the study by Samastı *et al.* [54] and are accessible through the published source at https://doi.org/10.3390/su16072881. The input matrices used in this study are also reported in the manuscript. The executable MATLAB code and intermediate computational matrices required to reproduce the results are provided in the Supplementary Material.

Declaration of competing interest

The authors declare no competing interests.

Funding

No funding was received for this research.

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