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Comprehensive Evaluation of Tailings Storage Facility Site Selection Based on AHP–TOPSIS: An Engineering Case Study

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Featured Application

The proposed AHP–TOPSIS framework provides a feasibility-stage decision-support workflow for ranking pre-screened tailings storage facility sites by integrating heterogeneous economic, engineering, and social project data into a transparent multi-criteria evaluation supported by robustness assessment and engineering interpretation.

Abstract

Tailings storage facility (TSF) site selection requires the simultaneous consideration of economic, engineering, safety, and social factors. Taking a copper-polymetallic mine in northern China as an engineering case, this study develops a feasibility-stage decision-support framework combining the analytic hierarchy process (AHP) and the technique for order preference by similarity to an ideal solution (TOPSIS) to evaluate six pre-screened candidate sites using 11 indicators. The relative closeness coefficients of Schemes I–VI were 0.5345, 0.4996, 0.4949, 0.3543, 0.4407, and 0.6125, respectively, resulting in the ranking VI > I > II > III > V > IV. Scheme VI was therefore identified as the preferred alternative. Robustness analyses considering weight uncertainty, ordinal-indicator coding, normalization, and alternative ranking procedures generally preserved the preferred-site identification; Scheme VI ranked first in 99.31% of 100,000 Monte Carlo simulations, and MOORA and EDAS produced the same complete ranking as TOPSIS. The ranking was also consistent with the project feasibility-study recommendation. The study provides a transparent and robustness-oriented workflow for comparative TSF site selection at the feasibility stage rather than proposing a new MCDM algorithm.

Keywords: AHP–TOPSIS; tailings storage facility site selection; multi-criteria decision-making; feasibility-stage decision support; robustness analysis

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1. Introduction

Tailings storage facilities are key mine-production facilities used for the centralized storage of beneficiation tailings and are characterized by high potential energy and high environmental risk. Once instability or dam failure occurs, major casualties and regional ecological damage may result [1,2]. Typical accident mechanisms include slope-sliding failure [3], foundation instability [4,5], and overtopping failure [6,7]. Accident-cause analyses indicate that inappropriate siting is one of the fundamental causes. TSF siting must comprehensively consider economic and technical factors such as distance from the processing plant, pumping head, and construction and installation cost, while also considering social factors such as land acquisition area, the number of households requiring relocation, and distance from residential areas. How to achieve scientific site selection under multiple constraints is therefore an important practical problem in mining engineering [8]. From a risk-management perspective, TSF site selection provides an early opportunity to reduce exposure to unfavorable engineering, hydrogeological, flood-control, and social conditions before detailed design measures are introduced. The proposed framework therefore supports risk-informed comparison among pre-screened alternatives, while remaining distinct from a formal quantitative risk assessment.

To address these issues, Chinese researchers have conducted studies on the construction of evaluation indicator systems, indicator weighting, and scheme optimization. Ling et al. established a database for environmental and natural-disaster risk assessment of tailings facilities, providing a reference for the integrated quantification of multi-source risk factors [9]. Zhang et al. applied Vague-set theory to convert different types of evaluation indicators into Vague values and calculated the similarity between candidate TSF sites and the ideal scheme under multiple indicators [10]. Quan and Sun used fuzzy AHP to establish a TSF risk-evaluation system involving facility attributes, the surrounding environment, geological background, and routine management [11].

Researchers outside China have also studied topics related to TSF siting. Al-Abadi et al. integrated geographic information systems with Entropy-TOPSIS and AHP–TOPSIS to evaluate the suitability and priority of multiple candidate sites [12]. Wamyil et al. used GIS-AHP and combined indicators including soil permeability, slope, road distance, and distance to water bodies to perform site-suitability evaluation through indicator weighting and spatial overlay [13]. Fortuna et al. systematically analyzed the effects of groundwater and seepage conditions on TSF design and management [14]. Clarkson and Williams summarized conventional geotechnical failure mechanisms of tailings dams and highlighted their implications for safe TSF design [15].

From a methodological perspective, criteria-weighting approaches in MCDM can generally be categorized as subjective, objective, and hybrid methods. Subjective approaches such as AHP explicitly incorporate expert knowledge and provide an interpretable pairwise-comparison structure, but their results depend on professional judgment, and the elicitation burden increases as the number of criteria grows. Objective weighting methods derive criterion importance from the statistical or information characteristics of the decision data, whereas hybrid approaches combine expert judgment with data-driven information [16,17]. Recent reviews have emphasized that different weighting strategies have distinct advantages and limitations and that their suitability depends on the decision context, data availability, and uncertainty characteristics [16,17]. Similarly, ranking models based on different aggregation or compromise principles may respond differently to criterion scaling and trade-offs. These methodological considerations highlight the importance of examining whether the preferred alternative remains stable under changes in weighting and ranking assumptions.

Overall, substantial progress has been made in TSF risk assessment, engineering site optimization, and multi-criteria decision-making. Nevertheless, the decision context addressed by much of the existing literature differs from the practical problem considered here. Risk-assessment studies primarily characterize environmental or safety risk levels of tailings facilities [9,11], whereas GIS-based studies emphasize regional spatial-suitability screening and overlay analysis [12,13]. Other MCDM applications have demonstrated the utility of AHP, TOPSIS, and related methods for engineering scheme selection and site-selection problems [18–20], and TOPSIS has also been applied specifically to comparative TSF site selection [21]. Building on this application context, the present study focuses on the feasibility-stage comparison of a finite set of pre-screened TSF alternatives using heterogeneous project-specific information. At this stage, decision makers require not only a quantitative ranking but also a transparent explanation of the weighting and ranking process, together with evidence that the preferred alternative is not overly dependent on particular modeling assumptions. This decision-support need motivates the present study.

Accordingly, this study takes the site selection of a TSF for a copper-polymetallic mine in northern China as the research object. The contribution of the study lies in structuring an application-oriented feasibility-stage decision-support workflow rather than in proposing a new MCDM algorithm. Specifically, (1) 11 heterogeneous indicators derived from project investigation and feasibility-study data are integrated at the individual-indicator level to compare six pre-screened candidate sites; (2) AHP and TOPSIS are combined to make expert weighting and alternative ranking explicit and traceable while maintaining a clear distinction between thematic indicator classification and the weighting structure; and (3) the stability of the preferred alternative is examined through a multi-dimensional robustness assessment covering uncertainty in criterion weights and selected modeling assumptions, followed by engineering interpretation and comparison with the feasibility-study recommendation. In this way, the study provides a transparent link between preliminary site screening and quantitative comparison among candidate TSF alternatives at the feasibility stage.

2. Materials and Methods

2.1. Study Area and Candidate TSF Sites

The engineering case considered in this study is a tailings storage facility (TSF) for a copper-polymetallic mine located in Xianghuang Banner, Inner Mongolia Autonomous Region, northern China. The processing capacity of the mine is 2000 t/d in Phase I and 2500 t/d in Phase II, with a designed service life of 17 years. During the mine service life, approximately 4.623×10^6 t of tailings, corresponding to approximately 3.188×10^6 m^3, are expected to be deposited in the TSF.

The study area is characterized by densely distributed mining rights, which considerably restrict the availability of suitable locations for TSF construction. The preliminary site screening was conducted on the basis of project topographic information, surrounding mining-right conditions, and the general engineering requirements for TSF siting. The available topographic information included 1:10,000 and 1:1000 project topographic maps as well as supplementary topographic information for the mine and its surrounding area.

Based on the preliminary site-selection principles adopted in the project feasibility study, six candidate TSF sites were identified within approximately 5 km of the mine. The candidate sites differ in transportation distance, topographic and geological conditions, storage capacity, dam geometry, catchment characteristics, construction and installation cost, land acquisition, relocation requirements, and proximity to residential areas. These differences provide the basis for the subsequent multi-criteria evaluation.

The principal evaluation data for the six candidate sites are presented in Table 1.

2.2. Establishment of the Comprehensive Evaluation Index System for TSF Site Selection

TSF site selection is a typical multi-criteria engineering decision problem involving economic feasibility, engineering safety, and social impacts. Because the relevant factors differ substantially in physical dimensions, data types, and relative importance, site selection based solely on engineering experience or individual indicators may not adequately represent the overall suitability of a candidate site.

The evaluation indicators were selected according to the following principles: (1) the indicators should have a meaningful influence on TSF site-selection decisions; (2) the required information should be obtainable from engineering investigations, feasibility-study data, or other project records; (3) indicators with substantial informa-

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tion overlap should be avoided to reduce redundancy; and (4) the indicator system should jointly reflect the principal economic, technical, and social constraints associated with TSF siting.

Table 1. Indicator system and thematic classification for comprehensive TSF site-selection evaluation.

Evaluation Objective	Indicator Dimension	Indicator	Scheme I	Scheme II	Scheme III	Scheme IV	Scheme V	Scheme VI
Comprehensive evaluation of TSF site-selection schemes O	Economic factors	Distance from processing plant (X_1)	2.4 km	3.5 km	3.6 km	2.7 km	2.1 km	0.9 km
		Pumping head (X_2)	100 m	110 m	100 m	80 m	100 m	30 m
		Construction and installation cost (X_3)	1.7703×10^8 CNY	1.2056×10^8 CNY	1.9025×10^8 CNY	1.6125×10^8 CNY	1.5960×10^8 CNY	1.0688×10^8 CNY
	Technical factors	Surrounding rock classification (X_4)	Grade II	Grade IV	Grade I	Grade II	Grade II	Grade III
		Hydrogeological conditions (X_5)	3	4	4	1	2	5
		Storage capacity (X_6)	5.07×10^6 m^3	4.55×10^6 m^3	5.31×10^6 m^3	4.63×10^6 m^3	4.44×10^6 m^3	4.36×10^6 m^3
		Dam height (X_7)	20 m	23 m	18 m	22 m	18 m	38 m
		Catchment area (X_8)	1.414 km^2	1.027 km^2	1.093 km^2	3.425 km^2	1.980 km^2	0.680 km^2
	Social factors	Land acquisition area (X_9)	58.3 ha	46.5 ha	66.8 ha	58.9 ha	60.0 ha	32.5 ha
		Households for relocation (X_{10})	10	13	20	18	40	0
		Distance from residential areas (X_{11})	1.1 km	1.2 km	0.2 km	0.3 km	1.4 km	2.6 km

Accordingly, the evaluation indicators were organized into three thematic dimensions: economic, technical, and social dimensions. These dimensions were used to classify the indicators according to their engineering implications rather than to define separate weighting levels in the AHP model. A total of 11 evaluation indicators were included: distance from the processing plant (X_1), pumping head (X_2), construction and installation cost (X_3), surrounding rock classification of the reservoir area (X_4), hydrogeological conditions of the reservoir area (X_5), storage capacity (X_6), dam height (X_7), catchment area (X_8), land acquisition area (X_9), number of households requiring relocation (X_{10}), and distance from residential areas (X_{11}). The resulting indicator system is shown in Figure 1.

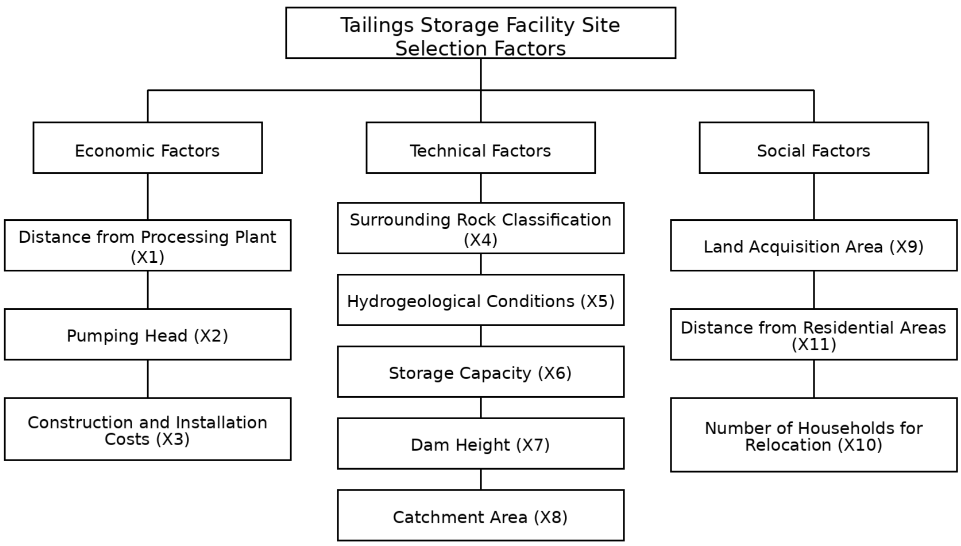

Figure 1. Comprehensive evaluation index system for TSF site-selection factors.

For the economic dimension, distance from the processing plant (X_1) directly affects the length and operational requirements of the tailings-transport system. Pumping head (X_2)

influences pumping-energy consumption and the configuration of the tailings-transport system. Construction and installation cost (X_3) reflects the combined economic effects of site conditions, dam construction, drainage works, seepage-control works, tailings transportation, and other major engineering components. These indicators therefore represent the principal economic differences among the candidate alternatives.

For the technical dimension, surrounding rock classification (X_4) reflects rock-mass quality and is associated with foundation stability, constructability, and geological conditions. Hydrogeological conditions (X_5) represent the inherent hydrogeological suitability of each candidate site and are related to groundwater occurrence, seepage potential, and groundwater-related engineering and environmental risks. Storage capacity (X_6) determines whether a candidate site can accommodate the required volume of tailings over the mine service life. Dam height (X_7) affects construction difficulty, stability requirements, and the potential consequences of dam failure. Catchment area (X_8) is directly related to the amount of storm runoff entering the reservoir area and therefore affects flood-control requirements.

For the social dimension, land acquisition area (X_9) reflects the extent of land required for TSF construction and may affect land-use coordination and compensation requirements. The number of households requiring relocation (X_{10}) represents the direct social and implementation impacts associated with population relocation. Distance from residential areas (X_{11}) reflects the spatial separation between the TSF and nearby communities and is therefore an important indicator of potential public-safety consequences.

During indicator screening, indicators with substantial information overlap were not included separately. For example, foundation bearing capacity and rock-mass quality may reflect partially overlapping geological characteristics; therefore, foundation bearing capacity was not retained as an additional independent indicator. The final indicator system was designed to retain the principal engineering constraints while avoiding excessive information redundancy.

Potential overlap among the retained indicators was further considered from the perspective of engineering meaning and decision role. Criteria were retained when they represented distinct project consequences, even where some dependence could arise from common site conditions. Accordingly, the screening process was intended to avoid obvious information redundancy rather than to require complete statistical independence among all criteria.

The final indicator set does not imply that all factors relevant to detailed TSF safety assessment are fully represented. Seismic hazard, long-term climatic variability, detailed water-quality conditions, and other design-specific environmental parameters were not introduced as separate criteria because consistently comparable data at the required level of detail were not available for all six alternatives at the feasibility-study stage; these factors remain important for subsequent detailed investigation, design, and environmental assessment.

2.3. Data Sources and Quantification of Evaluation Indicators

The evaluation data were compiled from the project feasibility study, topographic information, engineering measurements, and available project investigation records. The feasibility study provided the principal comparative information for the six candidate sites, including distance from the processing plant, catchment area, dam height, storage capacity, construction and installation cost, land-use characteristics, and the major engineering advantages and disadvantages of each alternative. Additional engineering and site-investigation information was used where necessary to quantify the remaining evaluation indicators.

Among the 11 indicators, X_1, X_2, X_3, X_6, X_7, X_8, X_9, X_{10}, and X_{11} were represented by quantitative values. The qualitative indicators X_4 and X_5 were converted into ordinal numerical scores to enable their incorporation into the TOPSIS decision matrix.

Surrounding rock classification (X_4) was evaluated with reference to the engineering rock-mass classification principles specified in the Chinese Standard for Engineering Classification of Rock Mass (GB/T 50218—2014) [22]. To incorporate the qualitative rock-mass classes into the quantitative decision matrix, Grade I, Grade II, Grade III, and Grade IV were assigned ordinal scores of 4, 3, 2, and 1, respectively. Thus, a higher score represents more favorable rock-mass conditions for TSF construction.

Hydrogeological conditions (X_5) were treated as an inherent site characteristic rather than as a representation of subsequent engineering seepage-control measures. The evaluation was conducted with reference to the hydrogeological and engineering-geological investigation factors specified in the Chinese Exploration Specification of Hydrogeology and Engineering Geology in Mining Areas (GB/T 12719—2021) [23]. The assessment primarily considered groundwater depth, formation permeability, aquifer characteristics, geological structures, and potential seepage pathways. These factors collectively characterize the relative hydrogeological favorability of a candidate site for TSF construction [24].

For integration into the decision matrix, the qualitative assessment of X_5 was converted in this study into a five-level ordinal scale ranging from 1 to 5, with higher scores representing more favorable hydrogeological conditions. Engineering seepage-control measures introduced during subsequent facility design, such as geomembrane lining or full-area seepage-control systems, were not included in the scoring of X_5 because these measures are engineering interventions rather than inherent hydrogeological characteristics of the candidate site.

This treatment allows both qualitative and quantitative indicators to be incorporated into a unified decision matrix while maintaining a clear distinction between inherent site conditions and engineering measures adopted after site selection.

2.4. AHP-Based Determination of Indicator Weights

The analytic hierarchy process (AHP) was used to determine the relative importance of the 11 evaluation indicators. In the present study, AHP was applied directly at the indicator level, and the 11 indicators were compared within a single 11×11 pairwise-comparison matrix. The economic, technical, and social dimensions described in Section 2.2 were used only for thematic classification and were not assigned separate weights in the AHP calculation.

Three domain specialists were selected based on their professional backgrounds and research or engineering experience relevant to TSF site-selection decisions. Specialist 1 is an associate professor with a doctoral degree and more than 10 years of research and engineering experience in mine safety, mine backfill, and tailings safety and participated in the investigated engineering project. Specialist 2 is an associate professor with a doctoral degree in engineering and approximately 8–9 years of research and engineering experience in mine safety, rock-mass stability, and disaster prevention and mitigation and did not participate in the investigated project. Specialist 3 is an associate professor and master's supervisor with a doctoral degree in mining engineering and more than 10 years of research and engineering experience in mine safety, safe metal-mine extraction, and full-tailings backfill and did not participate in the investigated project. Their complementary professional backgrounds were considered appropriate for evaluating the economic, technical, safety-related, and social criteria involved in the TSF site-selection problem. Each specialist completed the pairwise-comparison assessment independently, without discussion or consensus adjustment with the other specialists.

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Each specialist evaluated the relative importance of the 11 indicators using Saaty's 1–9 pairwise-comparison scale. With 11 indicators, each specialist completed 55 unique pairwise comparisons. A value of 1 represents equal importance between two indicators, whereas values of 3, 5, 7, and 9 represent moderate, strong, very strong, and extreme importance of one indicator relative to another, respectively. Intermediate values of 2, 4, 6, and 8 were used when a judgment fell between two adjacent levels. Reciprocal values were assigned for reverse comparisons.

For each specialist, a reciprocal judgment matrix was established as

$$D^{(k)} = (d_{ij}^{(k)})_{n\times n}$$

where ${d_{ij}}^{(k)}$ denotes the judgment of specialist (k) regarding the relative importance of indicator (i) compared with indicator (j), and (n = 11).

The individual judgment matrices were aggregated using the geometric mean to obtain the group judgment matrix:

$$d_{ij} = \left(\prod_{k=1}^{K} d_{ij}^{(k)}\right)^{1/K}$$

where (K = 3) is the number of specialists participating in the assessment.

The indicator-weight vector was subsequently obtained using the maximum-eigenvalue method and normalized as

$$W = (w_1, w_2, \ldots, w_n)\ \sum_{j=1}^{n} w_j = 1$$

The logical consistency of the judgment matrices was evaluated using the consistency index (CI) and consistency ratio (CR):

$$CI = \frac{\lambda_{\max} - n}{n-1}$$

and

$$CR = \frac{CI}{RI}$$

where ($\lambda_{\max}$) is the maximum eigenvalue of the judgment matrix, (n) is the matrix order, and (RI) is the corresponding average random consistency index. A judgment matrix was considered to have acceptable consistency when (CR < 0.10). Consistency was examined for the individual judgments as well as for the aggregated group judgment matrix before the final weights were used in the subsequent TOPSIS analysis.

2.5. TOPSIS Evaluation Procedure

The technique for order preference by similarity to an ideal solution (TOPSIS) was used to comprehensively evaluate and rank the six candidate TSF sites. TOPSIS is a multi-criteria decision-making method in which alternatives are ranked according to their relative distances from a positive ideal solution and a negative ideal solution. An alternative is considered preferable when it is closer to the positive ideal solution and farther from the negative ideal solution [25].

2.5.1. Establishment of the Initial Decision Matrix

Let (m) candidate alternatives (A_1, A_2,. . ., A_m) constitute the alternative set

$$A = \{A_1, A_2, \ldots, A_m\}$$

and let (n) evaluation indicators (X_1, X_2,. . ., X_n) constitute the indicator set

$$X = X_1, X_2, \ldots, X_n$$

The value of indicator (j) for alternative (i) is denoted by (x_{ij}), where (i = 1, 2,. . ., m) and (j = 1, 2,. . ., n). The initial decision matrix is expressed as

$$A = (x_{ij})_{m\times n}$$

2.5.2. Preference-Direction Unification and Normalization

Because the 11 evaluation indicators differ in physical dimensions, measurement units, and preference directions, normalization was performed before the TOPSIS calculation. Min–max normalization was adopted for the baseline analysis because it maps the observed performance of each criterion onto a common 0–1 scale while preserving the monotonic ordering of the alternatives. This representation is intuitive for the present finite alternative set because the observed least- and most-favorable criterion values provide explicit reference points for comparative evaluation. However, because the choice of normalization method may affect the geometric distances used in TOPSIS, the robustness of the ranking to an alternative vector-normalization procedure was additionally examined in Section 2.8.

For benefit-type indicators, for which a larger value represents better performance,

$$b_{ij} = \frac{x_{ij} - \min\limits_i x_{ij}}{\max\limits_i x_{ij} - \min\limits_i x_{ij}}$$

For cost-type indicators, for which a smaller value represents better performance,

$$b_{ij} = \frac{\max\limits_i x_{ij} - x_{ij}}{\max\limits_i x_{ij} - \min\limits_i x_{ij}}$$

The normalized decision matrix is denoted as

$$B = (b_{ij})_{m\times n}$$

After normalization, all indicators have the same preference direction, such that a larger normalized value represents better performance.

In the present evaluation system, hydrogeological conditions (X_5), storage capacity (X_6), and distance from residential areas (X_{11}) were treated as benefit-type indicators. Surrounding rock classification (X_4) was treated as an ordinal favorable-condition indicator after conversion into numerical scores, such that a better rock-mass class corresponds to a higher score. Distance from the processing plant (X_1), pumping head (X_2), construction and installation cost (X_3), dam height (X_7), catchment area (X_8), land acquisition area (X_9), and number of households requiring relocation (X_{10}) were treated as cost-type indicators.

2.5.3. Establishment of the Weighted Normalized Decision Matrix

The normalized indicator values were multiplied by the corresponding AHP-derived weights to obtain the weighted normalized decision matrix:

$$C = (c_{ij})_{m\times n}, \qquad c_{ij} = w_j b_{ij}$$

2.5.4. Determination of the Positive and Negative Ideal Solutions

Because all indicators were transformed into the same preference direction during normalization, the positive ideal solution consists of the maximum weighted normalized value for each indicator, whereas the negative ideal solution consists of the corresponding minimum value:

$$C^{+} = \left\{\max_{i}(c_{ij})\right\}, \quad C^{-} = \left\{\min_{i}(c_{ij})\right\}$$

where (C^+) and (C^-) denote the positive and negative ideal solutions, respectively.

2.5.5. Calculation of Distances and Relative Closeness

The Euclidean distances of each alternative from the positive and negative ideal solutions were calculated as follows [26]:

$$d_i^{+} = \sqrt{\sum\nolimits_{j=1}^{n}(c_{ij} - c_j^{+})^2}, \quad d_i^{-} = \sqrt{\sum\nolimits_{j=1}^{n}(c_{ij} - c_j^{-})^2}$$

where (d_i^+) and (d_i^-) denote the distances from alternative (i) to the positive and negative ideal solutions, respectively, and (c_j^+) and (c_j^-) are the corresponding elements of the positive and negative ideal solutions [21].

The relative closeness of alternative (i) to the positive ideal solution was then calculated as

$$E_i = \frac{d_i^{-}}{d_i^{+} + d_i^{-}}$$

The relative closeness coefficient (E_i) ranges from 0 to 1. A larger value indicates that an alternative is closer to the positive ideal solution and farther from the negative ideal solution and therefore has better overall performance. The six candidate TSF sites were ranked in descending order of (E_i).

2.6. Weight Sensitivity and Monte Carlo Analysis

Because the indicator weights determined using AHP depend partly on professional judgment, sensitivity analysis is important for examining whether plausible variations in model inputs materially affect the resulting MCDM ranking [27]. Accordingly, two complementary weight-sensitivity analyses were conducted to examine the robustness of the TOPSIS ranking.

First, a one-at-a-time perturbation analysis was performed for distance from residential areas (X_{11}), which had the highest baseline AHP weight. The baseline weight of X_{11} was varied by −20%, −10%, +10%, and +20%. For each perturbation scenario, the weights of the remaining ten indicators were proportionally rescaled so that the sum of all weights remained equal to 1 while their relative proportions were preserved.

Let δ denote the perturbation coefficient of X_{11}. The perturbed weight of X_{11} was calculated as

$$w_{11}' = w_{11}(1+\delta)$$

and the remaining weights were adjusted according to

$$w_j' = w_j \frac{1 - w_{11}'}{1 - w_{11}}, \quad j \neq 11$$

In addition to the predefined ±20% perturbation scenarios, the weight of X_{11} was progressively reduced to identify the approximate threshold at which the highest-ranked alternative changed.

Second, a Monte Carlo global weight-perturbation analysis was conducted to account for simultaneous uncertainty in all 11 criterion weights. In each simulation, every baseline weight was independently multiplied by a random factor drawn from a uniform distribution U(0.8, 1.2), corresponding to a ±20% perturbation range. The perturbed weights were subsequently normalized so that their sum remained equal to 1:

$$\tilde{w}_j^{(r)} = w_j u_j^{(r)}, \quad u_j^{(r)} \sim U(0.8, 1.2)$$

$$w_j^{(r)} = \frac{\tilde{w}_j^{(r)}}{\sum_{j=1}^{11} \tilde{w}_j^{(r)}}$$

A total of 100,000 Monte Carlo simulations were performed. For each simulation, the weighted normalized decision matrix, ideal-solution distances, relative closeness coefficients, and ranking of the six alternatives were recalculated. Ranking robustness was evaluated using the probability of each alternative being ranked first, its mean rank, mean relative closeness coefficient, and the 2.5th–97.5th percentile interval of the simulated relative closeness coefficients.

For reproducibility, the pseudorandom-number generator was initialized with a fixed seed. The Monte Carlo analysis was performed using Python 3.11.9.

2.7. Sensitivity Analysis of Ordinal Indicator Coding

The numerical coding of ordinal indicators may influence MCDM results because assigning equally spaced numerical values to qualitative categories implicitly assumes equal intervals between adjacent levels. To examine whether the TOPSIS ranking depended on this assumption, an additional coding-sensitivity analysis was conducted for surrounding rock classification (X_4) and hydrogeological conditions (X_5).

The baseline ordinal scores of X_4 and X_5 were first expressed on a 0–1 scale while preserving their original preference order. Three monotonic transformations were then considered: a concave scale (γ = 0.5), the baseline linear scale (γ = 1), and a convex scale (γ = 2). For each ordinal indicator, the transformed score was calculated as

$$z_{ij}^{(\gamma)} = \left(z_{ij}^{(0)}\right)^{\gamma}, \quad \gamma \in \{0.5, 1, 2\}$$

where $z_{ij}^{(0)}$ denotes the baseline normalized ordinal score and $z_{ij}^{(\gamma)}$ denotes the transformed score. The concave and convex transformations modify the relative spacing between adjacent categories while preserving their original ordering.

The three coding schemes for X_4 were combined with the three coding schemes for X_5, resulting in nine coding scenarios. For each scenario, the normalized values of the remaining nine indicators and the baseline AHP weights were kept unchanged, and the TOPSIS calculation was repeated. The alternative coding scales and the complete results are provided in Tables S5 and S6, respectively.

2.8. Robustness Analysis of the Normalization Method

To examine whether the TOPSIS ranking depended on the normalization procedure, vector normalization was used as an alternative to the baseline min–max normalization. The same initial decision matrix, baseline ordinal coding of X_4 and X_5, and AHP-derived criterion weights were retained.

Under vector normalization, the normalized value of alternative i for criterion j was calculated as

$$r_{ij}^{(v)} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

where x_{ij} is the original criterion value and m is the number of alternatives. The normalized values were multiplied by the same AHP weights used in the baseline analysis. Because vector normalization does not itself transform all criteria to a common preference direction, criterion orientation was accounted for when defining the ideal solutions: the maximum value was used as the positive ideal for benefit-type criteria and the minimum value for cost-type criteria, with the opposite definitions used for the negative ideal solution. The subsequent distance and relative-closeness calculations followed the same TOPSIS procedure described in Section 2.5.

The robustness of the ranking was assessed by comparing the rankings obtained using min–max and vector normalization. Spearman's rank correlation coefficient and Kendall's rank correlation coefficient were additionally calculated to quantify the agreement between the two rankings.

2.9. Cross-Method Ranking Comparison

To examine whether the preferred-site selection depended on the use of TOPSIS as the ranking algorithm, two additional established MCDM methods, the Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) method [28] and the Evaluation based on Distance from Average Solution (EDAS) method [29], were applied to the same six alternatives. MOORA and EDAS were selected because they employ aggregation principles different from the ideal-solution-distance mechanism of TOPSIS, thereby providing complementary checks on algorithm-dependent ranking behavior.

For MOORA, the original decision matrix was first subjected to vector normalization:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

The overall MOORA assessment value was then calculated by subtracting the weighted contributions of cost-type criteria from those of benefit-type criteria:

$$y_i = \sum_{j \in B} w_j r_{ij} - \sum_{j \in C} w_j r_{ij}$$

where B and C denote the sets of benefit- and cost-type criteria, respectively. A larger y_i indicates a more favorable alternative.

For EDAS, the average solution for each criterion was first determined as

$$AV_j = \frac{1}{m} \sum_{i=1}^{m} x_{ij}$$

Benefit-type:

$$PDA_{ij} = \frac{\max(0, x_{ij} - AV_j)}{AV_j}$$

$$NDA_{ij} = \frac{\max(0, AV_j - x_{ij})}{AV_j}$$

Cost-type:

$$PDA_{ij} = \frac{\max(0, AV_j - x_{ij})}{AV_j}$$

$$NDA_{ij} = \frac{\max(0, x_{ij} - AV_j)}{AV_j}$$

$$SP_i = \sum_{j=1}^{n} w_j PDA_{ij}, \quad SN_i = \sum_{j=1}^{n} w_j NDA_{ij}$$

$$NSP_i = \frac{SP_i}{\max_i(SP_i)}$$

$$NSN_i = 1 - \frac{SN_i}{\max_i(SN_i)}$$

$$AS_i = \frac{1}{2}(NSP_i + NSN_i)$$

A larger appraisal score AS_i indicates a more favorable alternative. The rankings obtained using MOORA and EDAS were compared with the baseline TOPSIS ranking using Spearman's rank correlation coefficient and Kendall's τ.

3. Results

3.1. AHP Weighting Results

The individual pairwise-comparison judgments were aggregated using the geometric mean to obtain the group AHP judgment matrix. The resulting reciprocal judgment matrix and corresponding indicator weights are presented in Table 2.

Table 2. Group AHP reciprocal judgment matrix and indicator weights.

Indicator	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	Weight
X_1	1.0000	0.7937	0.6934	0.5503	0.3969	0.6300	0.5503	1.2599	0.5000	0.6300	0.4368	0.0565
X_2	1.2599	1.0000	1.0000	1.0000	0.5000	0.4368	0.6300	1.0000	1.0000	0.6300	0.4368	0.0660
X_3	1.4422	1.0000	1.0000	1.2599	0.6300	1.0000	0.5503	1.2599	0.8736	0.7937	0.5000	0.0774
X_4	1.8171	1.0000	0.7937	1.0000	0.7937	1.0000	0.5503	0.7937	1.0000	1.2599	0.5503	0.0796
X_5	2.5198	2.0000	1.5874	1.2599	1.0000	0.7937	1.2599	1.0000	1.2599	0.5503	0.5000	0.1002
X_6	1.5874	2.2894	1.0000	1.0000	1.2599	1.0000	1.0000	1.0000	1.4422	1.5874	0.7937	0.1066
X_7	1.8171	1.5874	1.8171	1.8171	0.7937	1.0000	1.0000	2.0000	1.2599	1.2599	0.7937	0.1138
X_8	0.7937	1.0000	0.7937	1.2599	1.0000	1.0000	0.5000	1.0000	1.0000	1.2599	0.4368	0.0776
X_9	2.0000	1.0000	1.1447	1.0000	0.7937	0.6934	0.7937	1.0000	1.0000	0.7937	0.6300	0.0812
X_{10}	1.5874	1.5874	1.2599	0.7937	1.8171	0.6300	0.7937	0.7937	1.2599	1.0000	0.5000	0.0908
X_{11}	2.2894	2.2894	2.0000	1.8171	2.0000	1.2599	1.2599	2.2894	1.5874	2.0000	1.0000	0.1504

The complete individual pairwise-comparison matrices of the three specialists are provided in Tables S1–S3, and the corresponding individual and aggregated consistency results are summarized in Table S4. The maximum-eigenvalue method was used to derive the indicator weights from the aggregated group judgment matrix. The CR values of the three individual judgment matrices were 0.02592, 0.05356, and 0.07518, respectively, all below the acceptable threshold of 0.10. The aggregated group judgment matrix also showed acceptable consistency, with λ_{max} = 11.28229, CI = 0.02823, RI = 1.51000, and CR = 0.01869. Therefore, the individual and aggregated judgment matrices satisfied the consistency requirement for subsequent TOPSIS analysis.

The resulting indicator-weight vector obtained from the aggregated matrix was

W = {0.0565, 0.0660, 0.0774, 0.0796, 0.1002, 0.1066, 0.1138, 0.0776, 0.0812, 0.0908, 0.1504}.

Among the 11 indicators, distance from residential areas (X_{11}) received the highest weight (0.150), followed by dam height (X_7, 0.114), storage capacity (X_6, 0.107), and hydrogeological conditions (X_5, 0.100). The lowest weight was assigned to distance from the processing plant (X_1, 0.057). Overall, the weighting results indicate that the assessment placed relatively greater emphasis on safety- and engineering-related factors while retaining economic and social considerations in the decision structure.

3.2. TOPSIS Evaluation Results

3.2.1. Normalized Decision Matrix

The initial decision matrix containing the 11 evaluation indicators for the six candidate TSF sites was normalized according to the preference direction of each indicator. After normalization, all indicators were transformed so that a larger value represented more favorable performance.

The resulting normalized decision matrix is presented in Table 3.

Table 3. Normalized decision matrix (B).

Scheme	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}
I	0.444	0.125	0.159	0.667	0.500	0.747	0.900	0.733	0.248	0.750	0.375
II	0.037	0	0.836	0	0.750	0.200	0.750	0.874	0.592	0.675	0.417
III	0	0.125	0	1	0.750	1	1	0.850	0	0.500	0
IV	0.333	0.375	0.348	0.667	0	0.284	0.800	0	0.230	0.550	0.042
V	0.556	0.125	0.368	0.667	0.250	0.084	1	0.526	0.198	0	0.500
VI	1	1	1	0.333	1	0	0	1	1	1	1

The normalized results show clear differences among the six alternatives. Scheme VI achieved the best normalized performance for distance from the processing plant (X_1), pumping head (X_2), construction and installation cost (X_3), hydrogeological conditions (X_5), catchment area (X_8), land acquisition area (X_9), number of households requiring relocation (X_{10}), and distance from residential areas (X_{11}). However, Scheme VI did not perform optimally for all technical indicators. In particular, its storage capacity (X_6) and dam height (X_7) were less favorable than those of several other candidate sites.

These results indicate that no single candidate site dominated all evaluation indicators, supporting the need for a multi-criteria comprehensive evaluation.

3.2.2. Weighted Normalized Decision Matrix and Ideal Solutions

The normalized decision matrix was combined with the AHP-derived indicator weights to obtain the weighted normalized decision matrix shown in Table 4.

Table 4. Weighted normalized decision matrix (C).

Scheme	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}
I	0.0251	0.0082	0.0123	0.0531	0.0501	0.0797	0.1024	0.0568	0.0201	0.0681	0.0564
II	0.0021	0.0000	0.0647	0.0000	0.0752	0.0213	0.0853	0.0678	0.0481	0.0613	0.0626
III	0.0000	0.0082	0.0000	0.0796	0.0752	0.1066	0.1138	0.0659	0.0000	0.0454	0.0000
IV	0.0188	0.0247	0.0269	0.0531	0.0000	0.0303	0.0910	0.0000	0.0187	0.0499	0.0063
V	0.0314	0.0082	0.0285	0.0531	0.0251	0.0090	0.1138	0.0408	0.0161	0.0000	0.0752
VI	0.0565	0.0660	0.0774	0.0265	0.1002	0.0000	0.0000	0.0776	0.0812	0.0908	0.1504

Note: Calculations were performed using unrounded normalized values and unrounded AHP weights; values shown in the table are rounded to four decimal places.

The weighted normalized matrix also helps explain the formation of the final ranking. Scheme VI shows strong weighted performance in several influential criteria, particularly X_{11}, together with favorable performance in X_1, X_2, X_3, X_8, X_9, and X_{10}, whereas its disadvantages in X_6 and X_7 reduce but do not offset these advantages. Thus, the final ranking reflects the combined weighted performance of multiple criteria rather than dominance by a single indicator.

Because all indicators had been transformed into the same preference direction during normalization, the maximum weighted value of each indicator constituted the positive ideal solution, whereas the corresponding minimum value constituted the negative ideal solution. The resulting positive and negative ideal solutions are presented in Table 5.

Table 5. Positive and negative ideal solutions of the weighted normalized decision matrix.

Ideal Solution	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}
C^+	0.0565	0.0660	0.0774	0.0796	0.1002	0.1066	0.1138	0.0776	0.0812	0.0908	0.1504
C^-	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

3.2.3. Relative Closeness and Ranking of Candidate Sites

The Euclidean distances from each candidate site to the positive and negative ideal solutions were calculated, and the corresponding relative closeness coefficients were obtained. The results are presented in Table 6.

Table 6. Distances to the ideal solutions and relative closeness coefficients of the candidate sites.

Scheme	Distance to Positive Ideal d_i^+	Distance to Negative Ideal d_i^-	Relative Closeness E_i
I	0.1617	0.1856	0.5345
II	0.1797	0.1793	0.4996
III	0.2111	0.2068	0.4949
IV	0.2348	0.1288	0.3543
V	0.2043	0.1610	0.4407
VI	0.1647	0.2603	0.6125

To provide a worked example linking the calculation procedure in Section 2.5 to the numerical results, Scheme I and criterion X_1 are used for illustration. X_1 is a cost-type criterion, for which the minimum and maximum values among the six alternatives are 0.9 km and 3.6 km, respectively. According to the cost-type min–max normalization, the normalized value for Scheme I is $(3.6 - 2.4)/(3.6 - 0.9) = 0.4444$, corresponding to Table 3. Multiplying the unrounded normalized value by the AHP weight of X_1 (0.0564655) gives 0.0250958, which is reported as 0.0251 in Table 4. Using the complete set of 11 weighted normalized values for Scheme I together with the positive and negative ideal solutions in Table 5 gives $d_1^+ = 0.161669$ and $d_1^- = 0.185637$, reported as 0.1617 and 0.1856 in Table 6. The corresponding relative closeness coefficient is $E_1 = 0.534506$, which is reported as 0.5345 in Table 6. This example directly connects the normalization, weighting, distance calculation, and final ranking results presented in Tables 3–6.

The relative closeness coefficients of Schemes I–VI were 0.5345, 0.4996, 0.4949, 0.3543, 0.4407, and 0.6125, respectively. The resulting ranking of the six candidate sites was therefore

$$\text{Scheme VI} > \text{Scheme I} > \text{Scheme II} > \text{Scheme III} > \text{Scheme V} > \text{Scheme IV}.$$

Scheme VI obtained the highest relative closeness coefficient and was therefore identified as the preferred candidate site. Scheme I ranked second, while Schemes II and III showed similar overall performance. Scheme IV had the lowest relative closeness coefficient, indicating the greatest overall distance from the positive ideal solution among the six alternatives.

3.3. Weight Sensitivity and Monte Carlo Analysis Results

To examine the robustness of the ranking result, the weight of distance from residential areas (X_{11}), which had the highest baseline weight, was varied by −20%, −10%, +10%, and

+20%. The remaining indicator weights were proportionally adjusted to ensure that the total weight remained equal to 1.

The adjusted weight vectors under the different perturbation scenarios are presented in Table 7.

Table 7. Indicator weights under X_{11}-weight perturbation.

X_{11} Weight Change	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}
−20%	0.0585	0.0683	0.0802	0.0824	0.1038	0.1104	0.1178	0.0803	0.0841	0.0940	0.1203
−10%	0.0575	0.0671	0.0788	0.0810	0.1020	0.1085	0.1158	0.0789	0.0827	0.0924	0.1353
Baseline	0.0565	0.0660	0.0774	0.0796	0.1002	0.1066	0.1138	0.0776	0.0812	0.0908	0.1504
+10%	0.0555	0.0648	0.0760	0.0782	0.0984	0.1047	0.1118	0.0762	0.0798	0.0892	0.1654
+20%	0.0545	0.0636	0.0747	0.0768	0.0967	0.1028	0.1098	0.0748	0.0784	0.0876	0.1804

The TOPSIS evaluation was repeated for each perturbation scenario. The resulting relative closeness coefficients and rankings are presented in Table 8.

Table 8. Relative closeness coefficients and rankings under X_{11}-weight perturbation.

X_{11} Weight Change	Scheme I	Scheme II	Scheme III	Scheme IV	Scheme V	Scheme VI	Ranking
−20%	0.5480	0.5059	0.5235	0.3733	0.4363	0.5952	VI > I > III > II > V > IV
−10%	0.5415	0.5029	0.5096	0.3641	0.4384	0.6035	VI > I > III > II > V > IV
Baseline	0.5345	0.4996	0.4949	0.3543	0.4407	0.6125	VI > I > II > III > V > IV
+10%	0.5271	0.4960	0.4798	0.3440	0.4432	0.6221	VI > I > II > III > V > IV
+20%	0.5195	0.4923	0.4643	0.3333	0.4458	0.6322	VI > I > II > III > V > IV

Under the predefined X_{11}-weight perturbation scenarios, Scheme VI remained ranked first and Scheme I remained ranked second. When the weight of X_{11} was reduced by 20%, the relative closeness coefficient of Scheme VI decreased from the baseline value of 0.6125 to 0.5952, whereas a 20% increase in the X_{11} weight increased its relative closeness coefficient to 0.6322. Changes were observed only in the ordering of Schemes II and III when the X_{11} weight was reduced.

To further examine the point at which the preferred alternative would change, the weight of X_{11} was progressively reduced beyond the predefined perturbation range while the remaining weights were proportionally rescaled. The ranking reversal occurred at an X_{11} weight of approximately 0.0550, corresponding to a reduction of approximately 63.4% from its baseline value of 0.1504. At this threshold, Schemes III and VI had nearly identical relative closeness coefficients of approximately 0.570. Therefore, the preferred alternative did not change within the investigated ±20% range and required a substantially larger reduction in X_{11} importance before a ranking reversal occurred.

The Monte Carlo global weight-sensitivity results are presented in Table 9.

The Monte Carlo analysis produced a similar robustness pattern when all 11 criterion weights were perturbed simultaneously. Scheme VI was ranked first in 99.31% of the 100,000 simulations, whereas Scheme I was ranked first in approximately 0.69% of the simulations. None of the remaining alternatives became the highest-ranked scheme within the investigated global perturbation range.

Scheme VI also had the lowest mean rank (1.007) and the highest mean relative closeness coefficient (0.6130). Its simulated relative closeness coefficient ranged from 0.5732 to 0.6543 between the 2.5th and 97.5th percentiles. These results indicate that the identification of Scheme VI as the preferred alternative is highly stable under simultaneous multiplicative weight perturbations generated from U(0.8, 1.2), followed by weight renormalization. Nevertheless, the small probability of Scheme I becoming the highest-ranked alternative indicates that the ranking is not mathematically invariant to all possible combinations of weight changes.

Table 9. Monte Carlo global weight-sensitivity results based on 100,000 simulations.

Scheme	Probability of Rank 1 (%)	Mean Rank	Mean E_i	2.5th Percentile	97.5th Percentile
I	0.694	2.0136	0.5345	0.5069	0.5626
II	0.000	3.4017	0.4996	0.4728	0.5268
III	0.000	3.5854	0.4952	0.4558	0.5348
IV	0.000	6.0000	0.3541	0.3201	0.3888
V	0.000	4.9922	0.4402	0.4073	0.4731
VI	99.306	1.0071	0.6130	0.5732	0.6543

3.4. Ordinal-Indicator Coding Sensitivity Results

The alternative monotonic representations of X_4 and X_5 changed the numerical relative closeness coefficients to some extent but did not change the ranking of the six candidate sites. Across all nine combinations of concave, linear, and convex coding schemes, the complete ranking remained as follows:

$$\mathrm{VI} > \mathrm{I} > \mathrm{II} > \mathrm{III} > \mathrm{V} > \mathrm{IV}.$$

Scheme VI remained the highest-ranked alternative under every investigated coding scenario, with its relative closeness coefficient ranging from 0.6021 to 0.6225. Scheme I consistently ranked second, whereas Scheme IV remained the lowest-ranked alternative. The complete scenario-specific results are reported in Table S6.

These results indicate that the preferred-site identification and the overall ranking are insensitive to the specific equal-interval assumption adopted for the baseline ordinal coding within the investigated monotonic transformations. This analysis does not imply that the ordinal categories constitute exact interval-scale measurements; rather, it shows that the principal decision result is preserved under substantially different order-preserving numerical representations.

3.5. Normalization-Method Robustness Results

The vector-normalization procedure produced different relative closeness coefficients from those obtained using min–max normalization, reflecting the influence of normalization on the geometric structure of the TOPSIS decision space. Nevertheless, Scheme VI remained the highest-ranked alternative, while Schemes I and II remained second and third, respectively. Scheme IV also remained the lowest-ranked alternative. The only ranking change occurred between the two intermediate alternatives, Schemes III and V.

The Spearman rank correlation coefficient between the two rankings was 0.9429, and Kendall's τ was 0.8667, indicating a high degree of ranking agreement. Therefore, although the numerical relative closeness coefficients and the ordering of two intermediate alternatives were affected by the normalization procedure, the identification of the preferred site and the ordering of the three leading alternatives were insensitive to the normalization method investigated.

The comparison of the TOPSIS results under the two normalization methods is presented in Table 10.

Table 10. Comparison of TOPSIS results under different normalization methods.

Normalization	Scheme I	Scheme II	Scheme III	Scheme IV	Scheme V	Scheme VI	Ranking
Min-max	0.5345	0.4996	0.4949	0.3543	0.4407	0.6125	VI > I > II > III > V > IV
Vector	0.5249	0.5228	0.4085	0.3038	0.4233	0.7681	VI > I > II > V > III > IV

3.6. Cross-Method Ranking Comparison Results

The three MCDM methods produced the same complete ranking of the six candidate sites: Scheme VI > Scheme I > Scheme II > Scheme III > Scheme V > Scheme IV. Scheme VI was therefore identified as the preferred alternative not only by TOPSIS but also by MOORA and EDAS.

The Spearman rank correlation coefficient between TOPSIS and MOORA was 1.0000, with Kendall's $\tau = 1.0000$. The corresponding coefficients between TOPSIS and EDAS were also 1.0000 and 1.0000, respectively. Thus, complete rank agreement was obtained among the three methods for the present decision matrix and AHP weighting structure. This cross-method consistency indicates that the preferred-site identification is not an artifact of the specific TOPSIS ranking algorithm used in the baseline analysis.

The cross-method comparison results are presented in Table 11.

Table 11. Cross-method comparison of the rankings obtained using TOPSIS, MOORA, and EDAS.

Scheme	TOPSIS E_i	Rank	MOORA y_i	Rank	EDAS AS_i	Rank
I	0.5345	2	−0.0365	2	0.5118	2
II	0.4996	3	−0.0462	3	0.4474	3
III	0.4949	4	−0.0774	4	0.2575	4
IV	0.3543	6	−0.1462	6	0.0198	6
V	0.4407	5	−0.0951	5	0.2173	5
VI	0.6125	1	0.0951	1	0.8267	1

4. Discussion

4.1. Interpretation of the Site-Selection Results

The AHP–TOPSIS evaluation ranked the six candidate TSF sites as Scheme VI > Scheme I > Scheme II > Scheme III > Scheme V > Scheme IV, with Scheme VI obtaining the highest relative closeness coefficient. This result indicates that Scheme VI provides the most favorable overall balance among the economic, technical, and social criteria considered in the evaluation.

The ranking should not be interpreted as indicating that Scheme VI is superior in every individual indicator. In fact, Scheme VI has the smallest storage capacity among the six alternatives and the greatest dam height. Nevertheless, it performs favorably in several other influential indicators, including distance from the processing plant, pumping head, construction and installation cost, catchment area, land acquisition area, relocation requirements, and distance from residential areas. The resulting ranking therefore reflects the compensatory nature of multi-criteria decision-making, in which disadvantages in individual criteria may be offset by favorable performance in other dimensions.

The contribution of the present work should be distinguished from several related research streams. Risk-assessment studies such as Ling et al. [9] and Quan and Sun [11] primarily evaluate environmental or safety risk levels of tailings facilities, whereas the present study addresses preference ranking among six pre-screened candidate sites. GIS-based suitability studies [12,13] focus on regional spatial screening and map overlay, while the current problem begins after preliminary screening and uses detailed feasibility-stage project data to discriminate among a finite set of alternatives. Broader AHP/TOPSIS applications have demonstrated their usefulness for engineering scheme and site selection [18–20], and TOPSIS has also been applied directly to comparative TSF site selection [21]. In the present study, these established tools are organized within a feasibility-stage workflow that links numerical ranking with project-specific engineering interpretation, multi-dimensional robustness assessment, and comparison with the feasibility-study recommendation. This distinction defines the application-oriented originality of the study without implying that AHP or TOPSIS themselves are new methods.

A further distinction can be made from fuzzy AHP–TOPSIS frameworks. For example, Biswas et al. [30] incorporated fuzzy numbers into AHP–TOPSIS to represent uncertainty and linguistic ambiguity in decision-maker assessments. Such an approach can be advantageous when criterion values or expert judgments cannot be represented reliably by precise values. In the present engineering case, however, most criterion values were obtained directly from feasibility-stage investigations and project records, while only two indicators required ordinal representation. A conventional AHP–TOPSIS structure was therefore retained to preserve direct traceability between project data, expert-derived weights, and the final ranking. The present framework is not claimed to be methodologically superior to fuzzy AHP–TOPSIS; rather, its contribution lies in combining a transparent engineering-data structure with explicit robustness assessment and project-specific interpretation for a finite set of pre-screened TSF alternatives.

The result also highlights the importance of considering technical and safety-related factors together with economic criteria. In particular, hydrogeological conditions, storage capacity, dam height, and catchment area influence the engineering feasibility and risk characteristics of a TSF. Previous studies have emphasized the importance of hydrogeological conditions, seepage behavior, and geotechnical failure mechanisms in the design and safe management of tailings facilities [14,15]. Incorporating such factors into the site-selection stage therefore provides a more comprehensive basis for preliminary engineering comparison.

4.2. Engineering Implications of the Preferred Scheme

The engineering characteristics of Scheme VI provide a practical explanation for its high overall ranking.

From an economic perspective, Scheme VI is located approximately 0.9 km from the processing plant, representing the shortest transport distance among the six alternatives. Its pumping head is also the lowest. These characteristics can reduce tailings-transport requirements, pumping-energy consumption, and operational complexity. In addition, its construction and installation cost is approximately CNY 1.0688×10^8, the lowest among the candidate schemes.

From a flood-control perspective, Scheme VI has a catchment area of approximately 0.68 km^2, also the smallest among the alternatives. A smaller catchment area generally reduces the volume of storm runoff entering the reservoir and therefore provides favorable conditions for flood-control design. According to the feasibility-study design, the proposed TSF adopts a drainage-well and culvert system, and both construction stages are designed according to a 200-year flood standard.

Scheme VI also performs favorably with respect to surrounding social receptors. No households require relocation according to the evaluation data, and its distance from residential areas is greater than that of the other candidate schemes. The feasibility study further indicates that no important roads or residential facilities are located within approximately 2 km downstream of the proposed site. These characteristics reduce the potential exposure of surrounding communities and infrastructure compared with several of the other alternatives.

However, Scheme VI also presents engineering challenges. Its final dam height is 38 m, the greatest among the six candidate sites. The feasibility-study design therefore adopts staged construction. The first-stage dam provides storage for the early operating period, while the second stage is raised using the downstream method to achieve the final design elevation. This arrangement allows storage capacity to be developed progressively over the mine service life.

Although Scheme VI has the smallest total storage capacity among the alternatives, the available capacity remains adequate for the proposed project. The final total storage capacity is approximately 4.361×10^6 m^3, and the corresponding effective storage capacity is approximately 3.489×10^6 m^3. This exceeds the approximately 3.188×10^6 m^3 of tailings expected to be deposited during the 17-year mine service life. Thus, the relatively small storage capacity does not constitute a limiting factor under the current production plan.

Environmental-protection measures are also incorporated into the engineering design of the preferred scheme. The feasibility study proposes a full-area seepage-control system incorporating an HDPE geomembrane and geotextile layers, together with a return-water system for recycling clarified tailings water. These measures are important for subsequent TSF design and operation but should be distinguished from the inherent hydrogeological conditions represented by X_5. In the present evaluation, X_5 represents natural site characteristics, whereas seepage-control facilities are engineering interventions implemented after site selection.

Overall, Scheme VI should therefore be understood as the alternative that achieves the most favorable overall compromise among economic efficiency, engineering conditions, social impacts, and project feasibility rather than as an alternative without technical disadvantages.

4.3. Consistency with the Feasibility Study and Robustness of the Decision

The AHP–TOPSIS ranking is consistent with the site-selection recommendation presented in the project feasibility study. The feasibility study identifies Site 6 as the first-choice alternative and Site 1 as the second-choice alternative, corresponding to the two highest-ranked schemes obtained in the present evaluation. The feasibility-study comparison emphasizes several characteristics that are also represented in the indicator system, including transportation distance, catchment area, land requirements, engineering quantities, investment, and surrounding receptors.

This agreement should, however, be interpreted as an engineering consistency assessment rather than as fully independent external validation. Some of the quantitative data used in the AHP–TOPSIS evaluation were derived from the same project investigation and feasibility-study information that supported the original engineering comparison. The agreement therefore mainly indicates that the proposed framework can translate the underlying engineering information into an explicit and traceable quantitative ranking.

The robustness analyses provide additional evidence regarding the stability of the preferred alternative. Under the local weight-sensitivity analysis, Scheme VI remained ranked first when the weight of X_{11} was varied by $\pm 20\%$, and a reversal of the highest-ranked alternative occurred only after the X_{11} weight was reduced by approximately 63.4% from its baseline value. The Monte Carlo analysis produced a consistent pattern under simultaneous perturbation of all criterion weights, with Scheme VI ranked first in 99.31% of 100,000 simulations. These results indicate that the preferred-site identification is not dependent on a small change in a single influential weight or on moderate simultaneous variation in the weighting structure.

Robustness was also examined with respect to other modeling choices. Alternative monotonic representations of the two ordinal indicators did not change the complete ranking of the six alternatives. Replacing the baseline min–max normalization with vector normalization preserved Scheme VI as the preferred alternative and retained the same three highest-ranked schemes, although Schemes III and V exchanged positions. The corresponding Spearman and Kendall rank correlations were 0.9429 and 0.8667, respectively. In addition, MOORA and EDAS produced the same complete ranking as the baseline TOPSIS analysis. Taken together, these checks indicate that the identification of Scheme VI as the preferred alternative is reasonably robust to the investigated variations in weights, ordinal coding, normalization, and ranking procedure. This robustness should nevertheless be interpreted within the present six-site engineering case rather than as evidence of universal invariance of the framework.

4.4. Practical Contribution, Applicability, and Limitations of the Proposed Framework

The proposed framework has several practical advantages for preliminary TSF site selection. First, AHP provides a structured procedure for incorporating professional judgment into the determination of indicator importance, while the consistency test provides a means of checking the logical coherence of the pairwise comparisons. Second, TOPSIS enables quantitative comparison of alternatives containing indicators with different dimensions and preference directions. Third, the entire evaluation process—from indicator selection and weighting to normalization and final ranking—is explicit and traceable.

These characteristics make the method particularly suitable for preliminary engineering situations in which several candidate sites must be compared under competing economic, technical, and social constraints. The framework may also provide an application reference for other multi-criteria site-selection problems in mining engineering.

Nevertheless, several limitations should be recognized.

First, the AHP weights depend partly on professional judgment. Although the three specialists completed the pairwise comparisons independently and all individual and aggregated judgment matrices satisfied the consistency requirement, a different specialist group could produce a different weighting structure [16,17]. The local and Monte Carlo sensitivity analyses reduce concern that the preferred alternative is driven by moderate weight variation, but they do not eliminate the underlying subjectivity of the weighting process. Future studies could compare subjective AHP weighting with objective or hybrid weighting approaches using additional engineering cases.

Second, although obvious information redundancy was considered during indicator screening, some degree of interdependence among the retained criteria may remain because several engineering and social characteristics arise from common site conditions. The present weighted-aggregation framework treats the criteria as separate decision attributes and does not explicitly model such dependence. Future studies using larger multi-project datasets could examine inter-criterion dependence more formally and assess whether dependence-aware weighting materially affects the ranking results.

In addition, uncertainty may also exist in the feasibility-stage engineering data and in the numerical representation of qualitative criteria. Although the alternative monotonic-coding analysis showed that the ranking was stable for X_4 and X_5 under the investigated transformations, these ordinal scores should not be interpreted as exact interval-scale measurements, and uncertainty in the raw engineering data was not propagated probabilistically in the present study.

Third, the evaluation represents site conditions primarily at the feasibility-study stage and is therefore essentially static. TSFs normally have long operating lives, during which extreme rainfall, changes in production scale, changes in tailings properties, and other external factors may alter engineering risks and decision priorities [31,32]. Future research

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could examine stage-specific, scenario-based, or life-cycle evaluation structures in which expert judgments are elicited only for the criteria relevant to each decision stage.

Fourth, TSF site selection is inherently a spatial decision problem, whereas the present AHP–TOPSIS model primarily uses tabulated engineering indicators. Spatial information was considered during preliminary candidate-site screening, but the model does not explicitly represent the spatial distributions of topography, geological structures, drainage systems, mining-right boundaries, or sensitive receptors. Integration with GIS-based spatial analysis could improve the visualization and spatial resolution of future assessments [33].

Fifth, the present study is based on a single engineering case. Geological, hydrogeological, climatic, environmental, and socioeconomic conditions vary substantially among mining regions. Further applications to TSFs with different geological settings, ore types, production scales, and environmental constraints are needed to assess the broader generalizability of the proposed indicator system and weighting structure.

Finally, the amount of detailed engineering-geological and hydrogeological information available during preliminary site selection may be limited. Detailed geological investigation, hydrogeological investigation, seepage analysis, dam-stability analysis, flood-control design, and environmental assessment remain necessary before final design and construction. The proposed AHP–TOPSIS model should therefore be regarded as a decision-support tool for comparative site selection rather than as a substitute for detailed engineering analysis.

5. Conclusions

This study developed an AHP–TOPSIS-based decision-support framework for the comparative evaluation of six pre-screened candidate TSF sites for a copper-polymetallic mine in Xianghuang Banner, Inner Mongolia, China. Based on the engineering case, the following conclusions can be drawn.

(1) A feasibility-stage TSF site-selection indicator system was established covering economic, technical, and social dimensions. Eleven indicators related to tailings transportation, construction cost, geological and hydrogeological conditions, storage and dam characteristics, catchment conditions, land use, relocation, and residential safety were incorporated into a unified evaluation framework.

(2) The baseline AHP–TOPSIS evaluation produced relative closeness coefficients of 0.5345, 0.4996, 0.4949, 0.3543, 0.4407, and 0.6125 for Schemes I–VI, respectively, resulting in the ranking Scheme VI > Scheme I > Scheme II > Scheme III > Scheme V > Scheme IV. Scheme VI was therefore identified as the preferred alternative. Its favorable overall performance is primarily associated with its short transportation distance, low pumping head, low construction and installation cost, small catchment area, absence of household relocation, and relatively large separation from residential areas, despite disadvantages including the greatest dam height and the smallest total storage capacity among the six alternatives.

(3) Engineering interpretation indicates that the effective storage capacity of Scheme VI remains sufficient for the expected tailings volume over the planned 17-year mine service life. The model ranking is also consistent with the feasibility-study recommendation, which identifies Site 6 and Site 1 as the first- and second-choice alternatives, respectively. This agreement should be interpreted as engineering consistency rather than fully independent external validation because part of the evaluation information originated from the same project investigation and feasibility-study data.

(4) The robustness analyses generally support the stability of the preferred-site identification. Scheme VI remained ranked first under the predefined ±20% perturbations of the highest-weighted criterion, and a reversal of the preferred alternative required

an approximately 63.4% reduction in the X_{11} weight. Under simultaneous weight perturbation, Scheme VI ranked first in 99.31% of 100,000 Monte Carlo simulations. Alternative monotonic coding of the ordinal indicators did not change the complete ranking. Vector normalization also retained Scheme VI as the preferred alternative and preserved the three highest-ranked schemes, while MOORA and EDAS produced the same complete ranking as the baseline TOPSIS analysis. These findings indicate that the preferred-site identification is reasonably stable under the investigated variations in weighting and modeling assumptions.

(5) The principal contribution of this study is therefore an application-oriented feasibility-stage decision-support workflow rather than a new MCDM algorithm. The framework provides a transparent means of integrating heterogeneous engineering information, expert weighting, comparative ranking, robustness assessment, and engineering interpretation for a finite set of pre-screened TSF alternatives. Its applicability remains subject to expert-dependent weighting, possible interdependence among criteria, static feasibility-stage conditions, limited spatial representation, and the use of a single engineering case. The specific criterion weights and ranking obtained in this case should not be transferred directly to other TSF projects; the framework is intended as a feasibility-stage decision-support tool and does not replace the detailed geotechnical, hydrogeological, environmental, hydraulic, seismic, and structural safety assessments required for final design and approval. Future research could examine stage-specific decision structures, in which only the criteria relevant to the corresponding planning, construction, or operational stage are elicited, and assess the transferability of the framework using additional engineering cases and spatial information where appropriate.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/app16189244/s1, Table S1: Pairwise-comparison judgment matrix of Specialist 1; Table S2: Pairwise-comparison judgment matrix of Specialist 2; Table S3: Pairwise-comparison judgment matrix of Specialist 3; Table S4: Consistency results of the individual and aggregated AHP judgment matrices; Table S5: Alternative monotonic coding scales used for ordinal-indicator sensitivity analysis; Table S6: TOPSIS results under alternative monotonic coding schemes for X_4 and X_5.

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Abbreviations

The following abbreviations are used in this manuscript:

TSF	Tailings storage facility
AHP	Analytic hierarchy process
TOPSIS	Technique for order preference by similarity to an ideal solution
MCDM	Multi-Criteria Decision-Making
HDPE	High-density polyethylene
GIS	Geographic information system
MOORA	Multi-Objective Optimization on the Basis of Ratio Analysis
EDAS	Evaluation based on Distance from Average Solution

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