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# Multi-criteria framework for ranking geological sites in underground hydrogen storage

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Underground hydrogen storage (UHS) is central to enabling a sustainable energy transition, providing a means to balance renewable intermittency through large-scale, long-duration storage. The success of such systems depends critically on site selection, which must integrate technical, economic, and environmental considerations. Here we apply seven multi-criteria decision-making methods to evaluate five storage options, salt caverns, lined rock caverns (LRCs), depleted oil reservoirs, depleted gas reservoirs, and saline aquifers, using 34 parameters. Across all methods, salt caverns emerge as the most suitable sites, followed by LRCs, while porous reservoirs and saline aquifers rank consistently lower. Analysis of parameter influence shows that 16 factors contribute positively to site suitability and 18 exert negative effects, underscoring the complexity of decision frameworks. This comparative assessment provides a transparent basis for risk evaluation and cost optimization, offering practical guidance for research, policy, and deployment of UHS.

### Environmental significance

Large-scale hydrogen storage is needed to support renewable energy, but choosing the wrong geological site can lead to leakage, water contamination, and loss of stored hydrogen. These risks make site selection an important environmental decision. This study evaluates five major geological settings using a transparent multi-criteria framework built on 34 technical, economic, safety, and environmental parameters. The results show that salt caverns and lined rock caverns are the most stable and low-risk options, while porous reservoirs and saline aquifers carry higher environmental uncertainty. This work supports safer and more responsible deployment of underground hydrogen storage as part of the energy transition.

## 1 Introduction

Underground hydrogen storage (UHS) is emerging as a key component of sustainable energy systems, providing long-duration storage to mitigate inter-day intermittency of renewable energy sources such as wind and solar.[1,2] Various settings, including abandoned mines, saline aquifers, depleted hydrocarbon reservoirs and salt caverns offer potential geological storage, each presenting unique opportunities and challenges.[3–5] While UHS holds great promise as an energy storage medium, its success hinges on rigorous site selection, technological innovation, and economic viability.[6–14] Site selection requires an evaluation of geotechnical and economic factors, including the availability of infrastructure and geological suitability.[15,16]

For example, Wyoming has been proposed as a promising region based on extensive energy resources and existing underground storage.[17] Ranking criteria vary significantly from study to study with various approaches taken. Key operational considerations for porous reservoir storage include hydrogen diffusion and mixing with other gases, which influence storage efficiency and recovery rates; research indicates that the effective diffusion coefficient of hydrogen decreases with increasing pressure and temperature.[18,19] Furthermore, microbial reactions and fluid–rock interactions between hydrogen and reservoir may impact storage performance and hydrogen purity.[20–22] Petrophysical property alteration caused by prolonged hydrogen exposure require further research to ensure the integrity of UHS operations.[6]

Economics is another key aspect. Cost optimization aims to maximize storage capacity and net present value through careful management of operational parameters.[23] Encouragingly, UHS in formations such as the Broom Creek saline aquifer, Williston Basin, North Dakota, USA, has demonstrated high recovery efficiencies, underscoring the potential for cost-effective hydrogen storage.[24]

Multi-criteria decision-making (MCDM) objectively ranks sites across many common criteria and is emerging as an

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effective methodology for selecting storage sites.[25] Numerous studies, summarized in Table 1, have demonstrated various approaches in evaluating UHS sites. For example, in Poland, a study combined MCDM with a deep learning framework to evaluate bedded salt formations for hydrogen storage;[26] this approach deployed a convolutional neural network (CNN), to assist in site selection. A separate analysis of the Polish Lowlands ranked saline aquifers based on geological and reservoir properties, emphasizing the critical attributes of caprock integrity and reservoir permeability.[27] Similarly, a case study in the Taranaki Basin, New Zealand applied an MCDM decision tree and matrix methodology to assess depleted hydrocarbon fields and saline aquifers, emphasizing parameters such as storage capacity and reservoir depth.[28] In the UK, researchers have applied a hybrid MCDM framework combining the Analytical Hierarchy Process (AHP) and a 'preference ranking organization method for enrichment of evaluation' (PROMETHEE) to rank 71 depleted gas reservoirs.[29] The UK study accounted for both technical and economic factors, including reservoir rock quality and proximity to renewable energy sources.

Other approaches, such as interval-valued intuitionistic fuzzy AHP, have also been proposed to evaluate hydrogen storage options with a focus on economic and environmental sustainability.[30] Additionally, the choice of cushion gases in porous reservoirs has been shown to influence operational outcomes.[31] For instance, using carbon dioxide ($CO_2$) enhances hydrogen purity, while methane ($CH_4$) and nitrogen ($N_2$) improve production rates.[32]

Innovative tools such as the OPERATE-H2 platform further support UHS decision-making by providing a user-friendly interface for reduced-order models to evaluate saline aquifer and depleted gas reservoir storage scenarios.[33] This tool incorporates sensitivity analysis to guide stakeholders in selecting suitable sites, with injection pressure, permeability, depth, thickness, and water saturation being the most influential factors on porous reservoir screening.

These diverse studies highlight the necessity of a criteria-driven, integrated, and objective approach to UHS site selection, ensuring optimal storage of hydrogen while balancing technical, economic, and environmental considerations.[34]

This paper takes a holistic approach to UHS site selection by integrating a comprehensive set of 34 parameters and evaluating five types of storage site. The application of MCDM methods to salt caverns, saline aquifers, depleted gas and oil reservoirs, and lined rock caverns (LRCs) bridges the gap between theoretical frameworks and practical implementation by incorporating diverse economic, technical, safety, and environmental criteria to ensure a balanced evaluation of each site's potential.

The use of the 34 selected parameters provides a comparative assessment of sites with differing geological and operational characteristics, allowing stakeholders to identify the most suitable for UHS sites based on factors critical to project feasibility, cost-efficiency, and environmental impact.

The research is intended to provide stakeholders with actionable insights. The methodologies and results presented here aim to contribute to the development of sustainable and efficient hydrogen storage solutions, further advancing efforts to mitigate climate change and achieve energy security.

Table 1 Overview of diverse methodologies for UHS site evaluation and feasibility assessment

| Research/study | Method | Purpose of study | Site type | Location |
|---|---|---|---|---|
| Derakhshani *et al.* (2024)[26] | MCDM with deep learning | Site selection | Salt cavern | Poland |
| Higgs *et al.* (2024)[28] | MCDM decision tree and matrix | Prospect analysis | Porous reservoirs | New Zealand |
| Harati *et al.* (2024)[29] | MCMD through AHP and PROMETHEE | Prospect ranking | Depleted gas reservoirs | United Kingdom |
| Dias *et al.* (2023)[35] | Thermodynamic simulation | Cavern integrity | Salt cavern | Brazil |
| Kiran *et al.* (2023)[36] | Reservoir simulation with CMG and analytical modeling | Site feasibility assessment | Depleted gas reservoir | India |
| Lankof & Tarkowski (2023)[37] | GIS-based MCDM | Site suitability | Salt cavern | Poland |
| Safari *et al.* (2023)[38] | Reservoir simulation with CMG | Site selection | Depleted gas reservoir | Japan |
| İlbahar *et al.* (2022)[39] | Decision-making trial and evaluation laboratory (DEMATEL) | Site selection | Simulation models | Turkey |
| Liu *et al.* (2020)[40] | Numerical simulation with FLAC | UHS feasibility evaluation | Salt cavern | China |
| Pamucar *et al.* (2020)[41] | Integrating trapezoidal fuzzy neutrosophic numbers (TrFNN) and multi-attributive ideal-real comparative analysis (MAIRCA) | Evaluating potential energy storage options | Simulation models | Romania |
| Iordache *et al.* (2019)[42] | Additive ratio assessment set (ARAS) and interval type-2 hesitant fuzzy set (IT2HFS) | Site selection | Salt cavern | Romania |

 

Table 2 Parameters influencing UHS site selection; 34 parameters are analyzed across five UHS site types salt cavern, saline aquifer, depleted gas reservoir, depleted oil reservoir, and line rock cavern. References are provided, ensuring the data's reliability and relevance to UHS projects

| Criterion number | Criterion | Effect direction | Data reference | Salt cavern | Saline aquifer | Depleted gas reservoir | Depleted oil reservoir | Lined rock cavern |
|---|---|---|---|---|---|---|---|---|
| 1 | Levelized cost of $H_2$ storage ($ $kg^{-1}$) | – | 44 | 1.61 | 1.29 | 1.23 | 1.23 | 2.77 |
| 2 | Capital expenditures (CAPEX) | – | 45 | Low | Low | Low | Low | High |
| 3 | Operating expenditures (OPEX) | – | 45 | Medium | Low | Low | Low | Medium |
| 4 | Specific investment | – | 46 | Medium | Low | Low | Low | High |
| 5 | Annual cycles | + | 46 and 47 | High | Low | Low | Low | High |
| 6 | Storage capacity | + | 46 and 48 | Medium | High | High | High | Low |
| 7 | Depth (m) | – | 3 and 48–51 | 400–1500 | 200–2300 | 300–2700 | 800 | 70–200 |
| 8 | Cushion gas | – | 5 and 52 | Low | Medium | Medium | Medium | Low |
| 9 | Working gas | + | 52 | High | Low | Medium | Medium | High |
| 10 | Geological tightness | + | 52 | Very high | Low | Very high | Very high | Low |
| 11 | Hydrogen purity | + | 53–56 | Very high | Medium | Low | Very low | Very high |
| 12 | Working gas capacity/Total gas capacity (%) | + | 47 | 70 | 20–50 | 50–60 | 50–60 | 85 |
| 13 | Micro-organism | – | 57 and 58 | Low to medium | Medium | Low to high | Low to high | Very low |
| 14 | Water cut | – | 57 | Very low | 80–90% | 30–70% | 30–70% | Very low |
| 15 | Back recovery efficiency | + | 59 | High | Low | Low | Low | High |
| 16 | General technical readiness level (TRL) | + | 54 | 8 | 3 | 3–6 | 3–6 | 5–6 |
| 17 | Porosity | + | 50 | Low | High | High | High | Low |
| 18 | Permeability | + | 48 | Very low | High | High | High | Low |
| 19 | Leakage risk | – | 52 | Low | High | High | High | Very low |
| 20 | Hydrogen loss | – | 55 and 57 | Very low | High | High | High | Very low |
| 21 | Withdrawal capacity | + | 53 | High | Medium | Medium | Medium | High |
| 22 | Withdrawal rate | + | 52 | High | Medium | Medium | Medium | High |
| 23 | Injection rate | + | 52 | High | Medium | Medium | Medium | High |
| 24 | Discharge rate | + | 5 and 15 | High | Medium | Medium | Medium | High |
| 25 | Operating pressure (bar) | – | 54 | 35–210 | 30–315 | 15–285 | 15–285 | 20–200 |
| 26 | Gas temperature (°C) | – | 44 and 60 | 37.75 | 34 | 50 | 41.95 | 37.75 |
| 27 | Availability of pre-existing facilities | + | 48 and 54 | Low | Low | Very high | Very high | Very low |
| 28 | Chemical and microbial reaction | – | 48 and 54 | Low | High | High | High | Very low |
| 29 | Chemical conversion rate | – | 15 | Low | High | Medium | Medium | Low |
| 30 | Seismic risk | – | 15 | Low | High | Medium | Medium | Low |
| 31 | Gas mixing | – | 48 | Very low | Medium | High | High | Very low |
| 32 | Hydrogen mixing | – | 57 | Very low | Low | High | High | Very low |
| 33 | Flexibility | + | 48 | High | Medium | Medium | Medium | High |
| 34 | Diffusion and fingering | – | 48 | None | Low | Low | Low | None |

## 2 Geological sites

Various types of sites are suitable for underground storage projects.[43] In this study, several geological sites with potential for UHS have been investigated, including salt caverns, saline aquifers, depleted gas reservoirs, depleted oil reservoirs, and LRCs. Each site type offers unique advantages and faces distinct challenges, making site selection a critical component of UHS projects. Details on the studied UHS sites and their characteristics are available in SI.

## 3 Methodology workflow

To perform a comprehensive analysis of potential sites for UHS, it is essential to gather diverse parameters that influence operations. This study evaluates economic, technical, safety, and environmental factors across five site types: salt caverns, saline aquifers, depleted gas reservoirs, depleted oil reservoirs, and LRCs. These site types represent a broad spectrum of geological and operational characteristics, ensuring a thorough examination.

### 3.1 Data gathering

Table 2 summarizes the 34 parameters considered in this research, covering critical aspects of UHS projects. Data was obtained from extensive research using reliable sources, with references provided in the table for verification. After validation, experts in UHS reviewed and selected accurate values for each parameter. These verified data values were then applied in the analysis. The final set of 34 parameters was established through

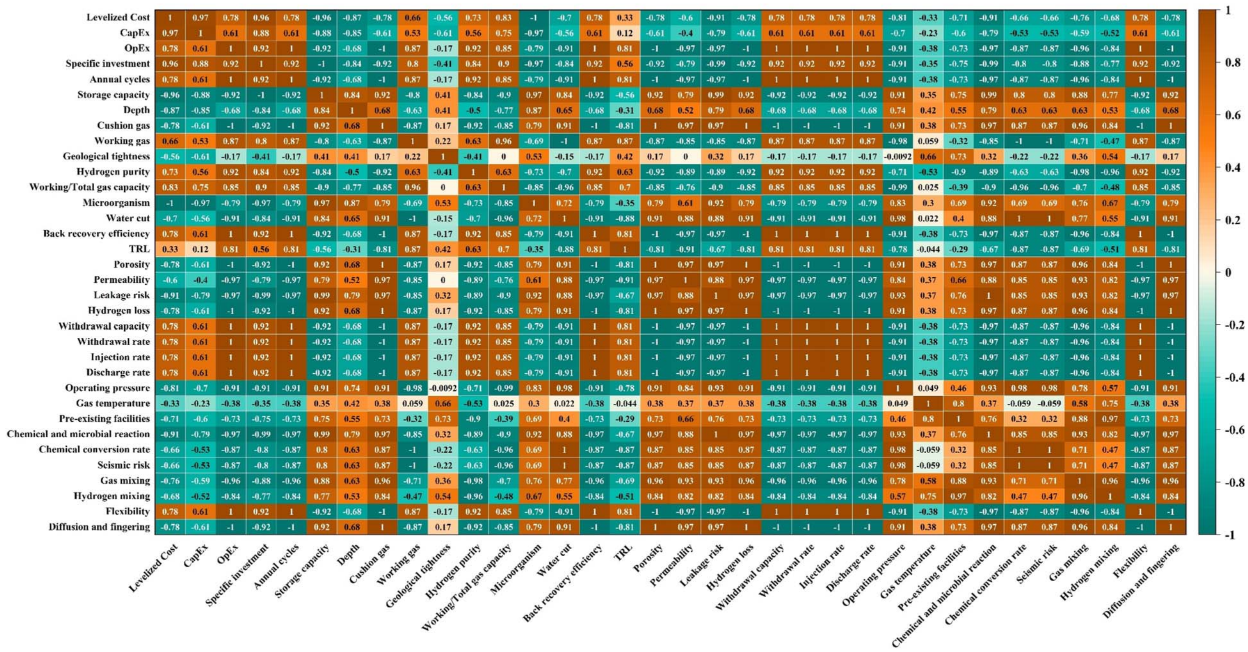


Fig. 1 The Pearson correlation coefficient of the used criteria.

an iterative process that combined literature review and expert judgment. The selection aimed to capture the most relevant technical, economic, safety, and environmental aspects affecting UHS feasibility. Only parameters that were consistently reported and measurable across all five geological site types were retained. Factors with limited data availability, high uncertainty, or strong site-specific dependence were excluded to ensure comparability and maintain a balanced decision matrix.

Fig. 1 shows the correlation between the parameters using the Pearson method. The Pearson method is a statistical measure that assesses the linear correlation between two variables. It quantifies both the strength and direction of the correlation, with values ranging from −1 to +1. A value of +1 indicates a perfect positive correlation, −1 indicates a perfect negative correlation, and 0 indicates no relationship. Additionally, figures illustrating the relationships between the parameters based on the Spearman and the Kendall method, SI Fig. 1 and 2.

### 3.2 MCDM

MCDM is a structured framework designed to evaluate and prioritize alternatives based on multiple criteria, making it

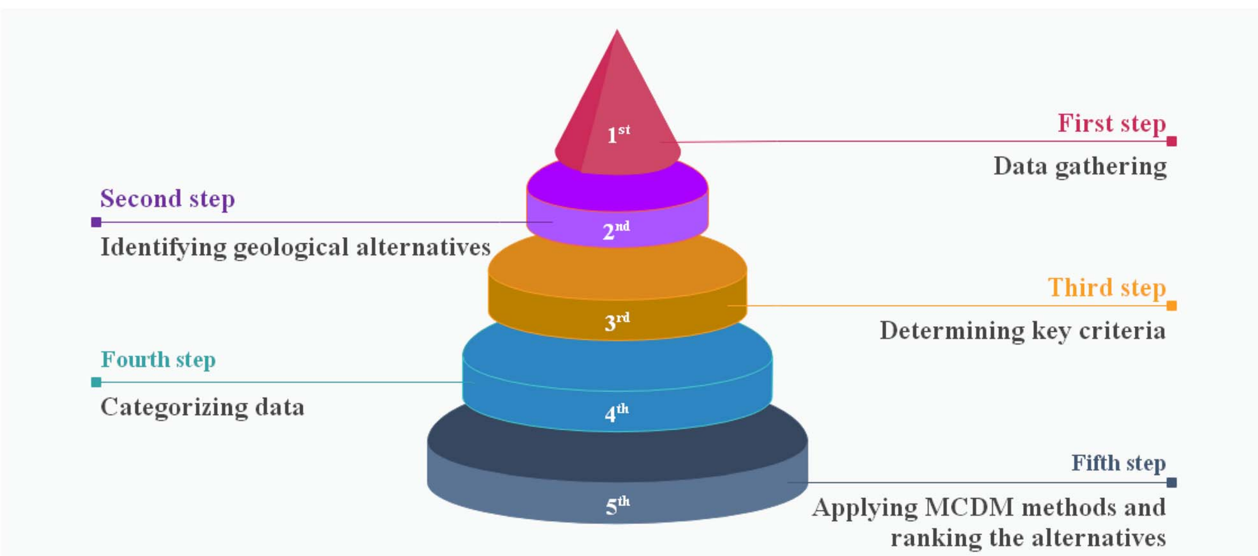


Fig. 2 MCDM workflow to select optimal UHS sites. The process involves data gathering, identifying geological alternatives, determining key criteria, categorizing data, applying MCDM methods, and ranking the alternatives.

Table 3 Transformation of qualitative descriptions into numerical values for MCDM analysis. Qualitative descriptions, ranging from "None" to "Very High," are assigned numerical values from 1 to 11 to ensure compatibility with MCDM methods for evaluating UHS site alternatives

| Qualitative description | None | Very low | Low | Medium | High | Very high |
|---|---|---|---|---|---|---|
| Assigned value | 1 | 3 | 5 | 7 | 9 | 11 |

particularly effective for complex decision-making scenarios. In the context of UHS, MCDM plays a pivotal role in systematically analyzing potential storage sites by integrating diverse economic, technical, and environmental factors. The MCDM process begins with defining decision objectives and identifying relevant criteria, ensuring alignment with the priorities and values of stakeholders.[61] Criteria are then weighted, often with expert input, to reflect their relative importance in the decision-making context.[62] This step ensures the analysis is tailored to the specific needs of decision-makers and stakeholders.[63] The weighting scheme was designed to maintain methodological neutrality and comparability among parameters. Equal weights were assigned to all criteria (0.029) following expert review, ensuring that no parameter group (technical, economic, environmental, or safety) disproportionately influenced the overall ranking. Storage capacity was given a slightly higher weight (0.043) to account for its fundamental importance in determining the potential and economic viability of UHS sites.

Alternatives are subsequently evaluated and scored based on their performance against each criterion. This involves constructing a scoring matrix and applying aggregation methods such as the weighted-sum model or fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) to rank the alternatives.[64] Sensitivity analysis is typically performed to assess the robustness of decisions against changes in criteria weights or scores, further enhancing the reliability and transparency of the process.[65]

Fig. 2 illustrates the MCDM workflow for selecting optimal UHS sites, providing a comprehensive approach that enhances transparency and accountability. The structured methodology ensures decision-makers can justify their choices, fostering stakeholder confidence.[66]

The flexibility of MCDM frameworks has led to their successful application in various domains, including healthcare prioritization and environmental management.[67] Within UHS, MCDM approaches have been utilized to optimize storage efficiency and sustainable energy infrastructure.[29] Studies have demonstrated their effectiveness in evaluating sites based on geological, technical, and economic criteria.[28] Risk management in hydrogen systems, incorporating hybrid MCDM frameworks, addresses critical issues such as environmental volatility and personnel training to mitigate risks in hydrogen storage and transportation.[68]

Collectively, these applications highlight the versatility of MCDM in supporting informed decision-making for UHS. By offering robust and adaptable solutions, MCDM enables the development of sustainable hydrogen storage systems globally, providing a foundation for a low-carbon energy future.[25]

## 4 Results and discussion

A total of 34 parameters were considered in this study (Table 2), encompassing both qualitative and quantitative descriptions. For qualitative criteria, a descriptive scale ranging from "None" to "Very High" was used. To integrate these qualitative parameters into MCDM methods, numerical values were assigned to each qualitative description. Table 3 outlines the corresponding numerical values, where the grade 'None' represents criteria with no valid data. The 1–11 scale was chosen to provide sufficient granularity for differentiating among qualitative categories while maintaining a simple and consistent numerical framework. The odd-numbered format offers a neutral midpoint, which helps balance the scoring process and ensures uniform interpretation across all MCDM methods.

The selection criteria outlined in Table 2 were applied across seven MCDM methods, SAW, TOPSIS, TODIM, ROV, PSI, PIV, and OCRA, to evaluate five site candidates: salt cavern, saline aquifer, depleted gas reservoir, depleted oil reservoir, and LRC. These site candidates serve as alternatives in the MCDM analysis. In the SI, a figure (SI Fig. 3) visually summarizes the relationships between the considered criteria and the site

Table 4 Rankings of UHS types based on the results of various MCDM methods. Salt caverns consistently rank as the most suitable option, while saline aquifer is ranked as least suitable. LRC ranks either first or second, with depleted oil and gas reservoirs ranking third and fourth respectively

| | MCDM method applied | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Rank | SAW | TOPSIS | TODIM | ROV | PSI | PIV | OCRA | Total |
| 1 | LRC | Salt cavern | Salt cavern | Salt cavern | LRC | Salt cavern | LRC | Salt cavern |
| 2 | Salt cavern | LRC | LRC | LRC | Salt cavern | LRC | Salt cavern | LRC |
| 3 | Depleted oil reservoir | Depleted oil reservoir | Depleted oil reservoir | Depleted oil reservoir | Depleted oil reservoir | Depleted oil reservoir | Depleted oil reservoir | Depleted oil reservoir |
| 4 | Depleted gas reservoir | Depleted gas reservoir | Depleted gas reservoir | Depleted gas reservoir | Depleted gas reservoir | Depleted gas reservoir | Depleted gas reservoir | Depleted gas reservoir |
| 5 | Saline aquifer | Saline aquifer | Saline aquifer | Saline aquifer | Saline aquifer | Saline aquifer | Saline aquifer | Saline aquifer |

 

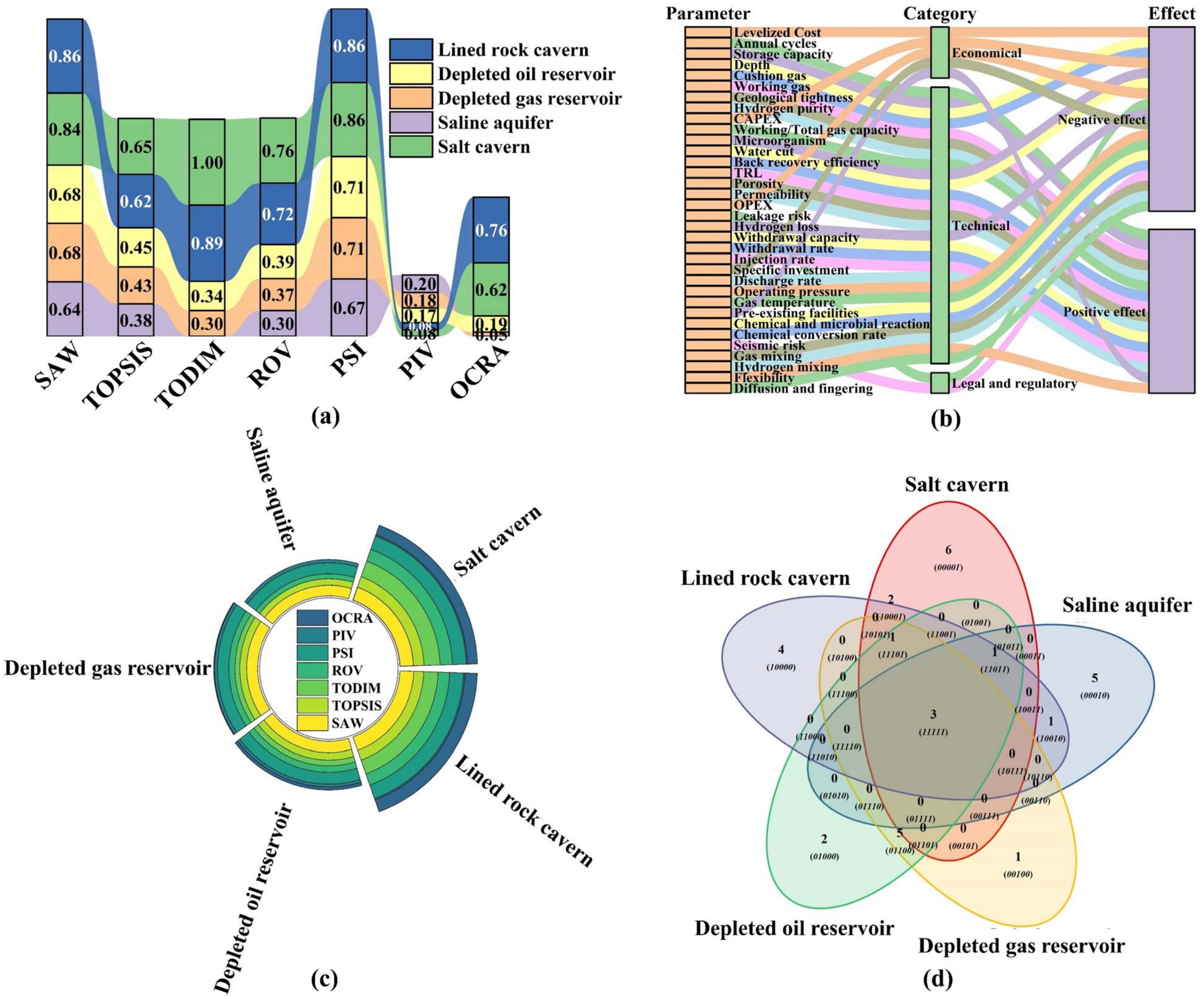


Fig. 3 (a) Ribbon diagram – scores and rankings assigned to each site type using various methods. (b) Alluvial diagram – categories of parameters (economical, technical, and legal/regulatory) and their positive or negative effects on the performance of the applied MCDM method. (c) Radial stack – scores assigned to each site by method. (d) Venn diagram – the relationship between various sites based on the results.

alternatives, providing a comprehensive overview of the decision-making framework for UHS site selection.

Criterion weighting plays a key role in determining the importance of individual parameters within the MCDM process. The outcomes of the MCDM techniques emphasize the flexibility of the approach, as the results can be adjusted based on the significance and impact (positive or negative) of each parameter. This adaptability ensures that the findings remain robust and aligned with specific project requirements or stakeholder priorities.

After selecting the desired criteria, alternatives, and methods, the most suitable site for UHS was identified. Table 4 presents the results of the various MCDM methods and their final score based on the selected criteria and site alternatives. The findings indicate that the salt cavern site is the most suitable option for hydrogen storage. In contrast, the saline aquifer site was ranked the lowest. The LRC site secured the second position, while the depleted oil reservoirs, depleted gas reservoirs, and saline aquifers were ranked third, fourth, and fifth, respectively. The consistently higher rankings of salt caverns and LRCs are primarily a result of their more favorable parameter values relative to the other geological formations. Both exhibit superior characteristics in key factors, which exert strong positive influence on the MCDM outcomes. Because the weighting scheme was nearly uniform, these variations in parameter performance were the dominant drivers of the final rankings, reflecting the inherent technical and operational advantages of cavern-based systems.

Once the rankings were obtained, it became essential to analyze how each criterion influenced the performance of the applied MCDM methods. Fig. 3 presents the analysis of results obtained from MCDM methods using various statistical techniques and indicators. Criteria can exert a positive, negative, or neutral (ineffective) impact on the methods' performance. Fig. 3(b) illustrates the results of this evaluation. Of the 34 analyzed criteria, 16 were found to positively influence the performance of the MCDM methods, while 18 criteria exhibited negative effects.

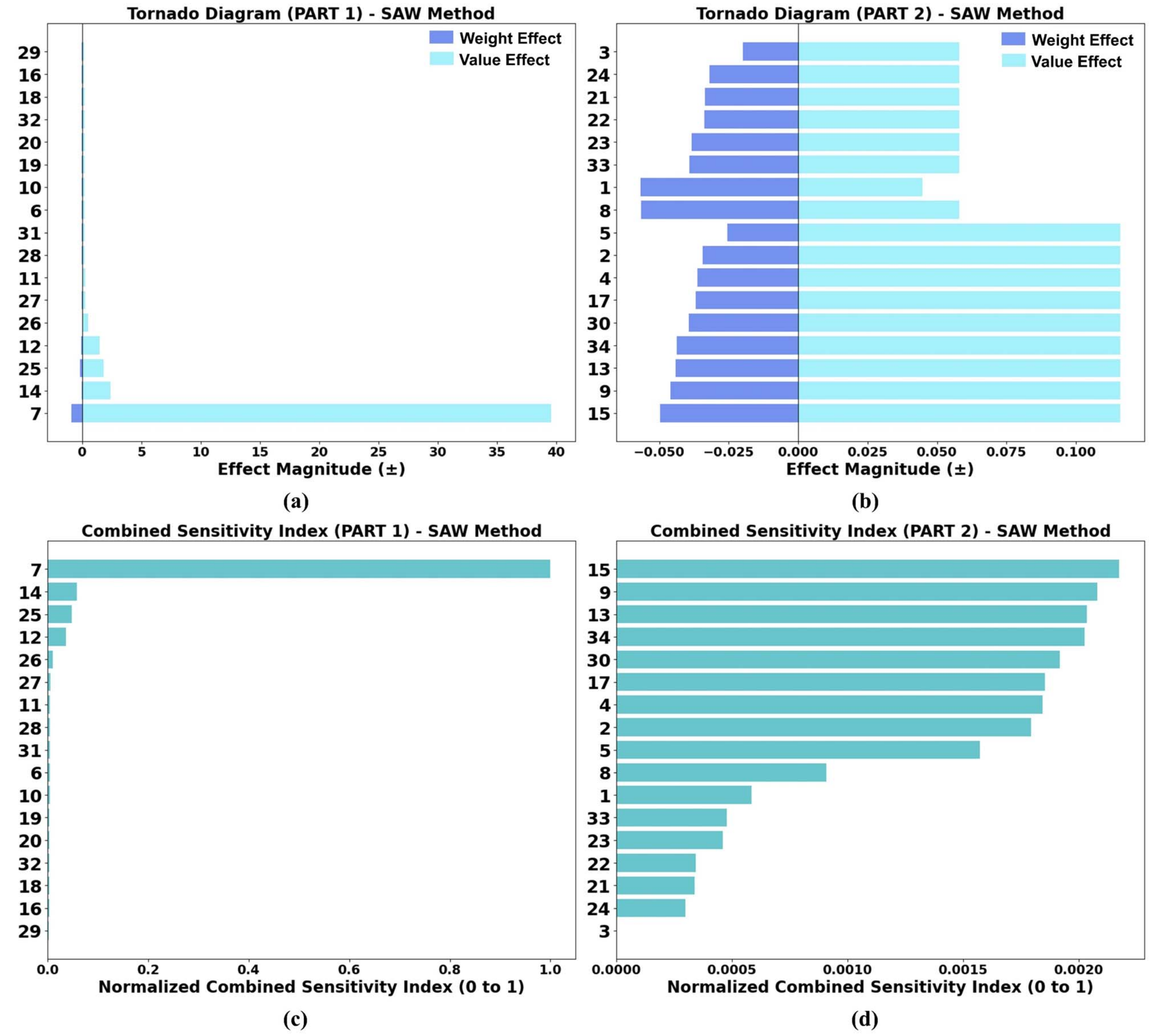


Fig. 4 Tornado diagrams and combined sensitivity indices for the SAW method, based on 10 000 Monte Carlo simulations. (a) and (b) depict the sensitivity of each criterion by displaying the effects of weight perturbation and value inputs variation. The parameters are split into two parts for better visualization and interpretation, due to the high number of criteria. (c) and (d) represents the normalized combined sensitivity index derived from the sum of weight and value effects, again divided into two parts. The vertical axis in all plots indicates the assigned numbers for the parameters (parameter indices), as outlined in Table 2.

This evaluation highlights the significance of understanding the influence of each criterion, as it enables decision-makers to refine the methods further by emphasizing parameters with positive contributions and mitigating the impact of those with negative influences. Furthermore, the environmental parameters play a decisive role in shaping the overall rankings of the geological formations. Criteria such as hydrogen loss, leakage risk, seismic risk, and chemical or microbial reactions tend to disadvantage porous formations like saline aquifers and depleted reservoirs, where higher permeability and microbial activity can lead to containment and purity challenges. In contrast, salt caverns and LRCs consistently benefit from their

Table 5 Sensitivity analysis results from Monte Carlo simulation

| | MCDM methods | | | | | | |
|---|---|---|---|---|---|---|---|
| Criteria effect | SAW | TOPSIS | TODIM | ROV | PSI | PIV | OCRA |
| Most | Depth | Depth | Operating pressure | Depth | Depth | Depth | Depth |
| Least | OPEX | Geological tightness | Withdrawal rate | Hydrogen purity | Levelized cost | Gas temperature | Hydrogen loss |

impermeable structures, minimal microbial influence, and low reactivity with hydrogen, which translate into higher environmental stability and safety.

After determining the results, a sensitivity analysis was conducted to evaluate the impact of each parameter on the outcomes of the various methods employed. This analysis was based on the values of each parameter and the weights assigned to them. The Monte Carlo simulation method was utilized for this analysis. The results of the sensitivity analysis for the SAW method are illustrated in Fig. 4. Detailed sensitivity analysis results for the TOPSIS, TODIM, ROV, PSI, PIV, and OCRA methods can be found in the (SI Fig. 4–9). Table 5 presents the sensitivity analysis results for the parameters of each method. The Monte Carlo simulations revealed that the Depth criterion had the most significant impact on the results of all MCDM methods.

The application of MCDM methods in UHS site selection faces several challenges and limitations. One major issue is restricted access to data related to various aspects of UHS operations, including technical, economical, chemical, physical, geological, safety, environmental, and social factors.[29,69] As UHS is an emerging field, available data is often incomplete, and access to existing data can be constrained.[7] These limitations can affect the robustness and reliability of MCDM techniques when applied to UHS studies. For instance, recent reviews have shown that the scarcity of reliable field data remains one of the main challenges in assessing UHS site suitability. Limited quantitative information on microbial activity, geochemical reactions, and caprock integrity, particularly in depleted reservoirs, can introduce significant uncertainty in parameter estimation and ranking accuracy. These gaps, as noted by Rooijen and Hajibeygi,[70] highlight the need for further pilot scale investigations to validate current assumptions and improve the robustness of multi criteria frameworks.

Assigning appropriate weights to criteria is a critical step in MCDM methods, as these weights directly influence the performance and outcomes of the decision-making process. Typically, experts in the field are responsible for assigning these weights based on their knowledge and experience.[71,72] Accurate determination of criteria weights is essential to reduce uncertainty and reflect stakeholder priorities, as improperly assigned weights can significantly impact the final results.[73]

The impact of each criterion on MCDM performance is another key consideration. As illustrated in Fig. 3(b), the influence of criteria can vary significantly, with some parameters exerting positive effects while others have negative impacts. This influence can be assessed either through automated systems or by expert decision-makers.[74] However, relying solely on automated systems may lead to incorrect decisions if the system misinterprets parameter relationships. Alternatively, expert-driven assessments must be performed with precision, carefully considering all relevant aspects to minimize uncertainty and ensure reliable outcomes.[75]

Despite these limitations, MCDM methods offer significant advantages and broad applications. Smart decision-making techniques optimize the UHS site selection process by reducing costs, minimizing risks, and effectively analyzing the relationships between parameters using mathematical frameworks.[76,77] These methods provide optimal and precise results, enabling informed decision-making and supporting stakeholders and policymakers across various domains, including UHS.[78] The results of this study provide a comprehensive framework for identifying and evaluating suitable UHS sites using advanced MCDM techniques. By considering a diverse set of parameters and site alternatives, this work bridges critical knowledge gaps in UHS site selection and highlights the robustness of MCDM approaches. The findings emphasize the superior suitability of salt caverns for hydrogen storage while demonstrating the adaptability of LRCs and the feasibility of depleted hydrocarbon reservoirs under certain conditions. Moreover, the evaluation of parameter effects underscores the importance of carefully weighing criteria that influence decision outcomes, paving the way for further refinements to enhance MCDM methodologies. Future research should focus on integrating real-time monitoring systems, expanding datasets, and incorporating advanced modeling techniques to address current limitations. Collaboration between researchers, industry stakeholders, and policymakers will be essential to translate these findings into actionable strategies, ensuring the safe, cost-effective, and sustainable implementation of UHS solutions on a global scale.

## 5 Conclusions

This study applied seven multi-criteria decision-making (MCDM) methods, SAW, TOPSIS, TODIM, ROV, PSI, PIV, and OCRA, to identify the most suitable site for underground hydrogen storage (UHS). A comprehensive set of 34 criteria, encompassing economic, technical, safety, and environmental aspects, was evaluated across five potential site types: salt caverns, saline aquifers, depleted gas reservoirs, depleted oil reservoirs, and lined rock caverns. The findings revealed that salt caverns emerged as the most suitable option for UHS, owing to their superior performance across multiple criteria, while saline aquifers were ranked lowest. Among the 34 criteria analyzed, 16 demonstrated a positive effect on the performance of the MCDM methods, while 18 had a negative impact. This highlights the flexibility of the employed approach, as the results can be refined based on the significance and influence of individual parameters. Additionally, this study facilitates the comparison of diverse geological sites, providing valuable insights into their relative suitability for hydrogen storage.

By leveraging MCDM techniques, this study streamlines the inherently complex process of UHS site selection, improving decision accuracy, reducing uncertainties, and offering potential cost and risk mitigation benefits. The robust and adaptable framework presented here serves as a foundation for future research and practical applications, supporting the development of sustainable hydrogen storage systems and advancing the global transition toward clean energy solutions. Ultimately, this work highlights the critical role of UHS in enabling renewable energy integration and achieving long-term climate goals, offering a scalable and reliable pathway toward decarbonized energy systems.

## Conflicts of interest

There are no conflicts to declare.

## List of abbreviations

| | |
|---|---|
| UHS | Underground Hydrogen Storage |
| MCDM | Multi-Criteria Decision-Making |
| LRC | Lined Rock Cavern |
| CAPEX | Capital Expenditure |
| OPEX | Operating Expenditure |
| SAW | Simple Additive Weighting |
| TOPSIS | Technique for Order of Preference by Similarity to Ideal Solution |
| TODIM | TOmada de Decisão Interativa Multicritério |
| ROV | Ratio of Optimization Values |
| PSI | Preference Selection Index |
| PIV | Proximity Indexed Value |
| OCRA | Operational Competitiveness Rating |
| AHP | Analytical Hierarchy Process |
| PROMETHEE | Peference Ranking Organization Method for Enrichment of Evaluations |
| GIS | Geographic Information System |
| CNN | Convolutional Neural Network |
| DEMATEL | Decision-Making Trial and Evaluation Laboratory |
| MAIRCA | Multi-Attributive Ideal-Real Comparative Analysis |
| ARAS | Additive Ratio Assessment |
| IT2HFS | Interval Type-2 Hesitant Fuzzy Set |
| TrFNN | Trapezoidal Fuzzy Neutrosophic Numbers |
| CMG | Computer Modelling Group |
| FLAC | Fast Lagrangian Analysis of Continua |
| $H_2$ | Hydrogen |
| $CO_2$ | Carbon Dioxide |
| $CH_4$ | Methane |
| $N_2$ | Nitrogen |
| CCUS | Carbon Capture, Utilization, and Storage |
| OECD | Organisation for Economic Co-operation and Development |
| TRL | Technical Readiness Level |

## Data availability

The data supporting this article are included within the main text, figures, and tables.

Supplementary information (SI) is available. See DOI: https://doi.org/10.1039/d5va00380f.

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