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Application of a novel multi-criteria decision analysis approach for evaluating the sustainability of contaminated site management: An example from China

Xiaonuo Li [a], Shiyi Yi [a,b], Weiping Chen [a,b], Andrew B. Cundy [c,*]

[a] Laboratory of Soil Environmental Science and Technology, Research Center for Eco-Environmental Sciences, Chinese Academy of Sciences, Beijing 100085, China
[b] College of Resource and Environment, University of Chinese Academy of Sciences, Beijing 100049, China
[c] GAU-Radioanalytical, School of Ocean and Earth Science, University of Southampton, Southampton SO14 3ZH, UK

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A B S T R A C T

The performance of contaminated site management in terms of its sustainability can be inherently uncertain, considering that this performance depends not only on individual site characteristics and variability, but also on integrated (and potentially long-term) environmental, social, economic and technical impacts. The present study proposes a combination weights-based TOPSIS model (Technique for Order Preference by Similarity to Ideal Solution), following a multi-criteria decision analysis (MCDA) approach, to quantitatively analyze the most influential measures and indices over the entire life cycle of contaminated site management (from site investigation to land reuse) in China. Results indicate that the sustainability performance of different sites varies widely due to differences in the best management practices (BMPs) implemented. Environmental dimensions in strategy design and remediation implementation processes contribute most to the overall sustainability performance when whole life-cycle management is considered, with social dimensions relatively under-emphasised. Based on a sensitivity analysis of the TOPSIS method, random variations of indices' weights did not result in significant alteration of the modelled sustainability performance of the evaluated sites, which indicates that the method provides a relatively robust approach. The MCDA approach developed enables stakeholders to adopt optimal BMPs for risk control and to enhance sustainability performance in contaminated site management, covering the whole life cycle of site remediation and redevelopment, although further work is required to determine its international applicability.

1. Introduction

Since 2000, the concept of sustainable development has increasingly been incorporated into environmental projects, including in contaminated site management via the growing development of sustainable remediation approaches (ITRC (Interstate Technology and Regulatory Council), 2011; Bardos et al., 2016; Naseri-Rad et al., 2022). Sustainable remediation is not only limited to the traditional risk management of pollutants (although this is at its core), but also focuses on a more integrated and balanced consideration of all pillars of sustainability over the whole life cycle of site remediation and redevelopment, including its wider effects involving disturbance to communities, ecological impacts during project implementation and economic income from employment opportunities, which may be ignored (or under-played) under more traditional risk-based management approaches (Ellis and Hadley, 2009; SuRF-UK (Sustainable Remediation Forum from United Kingdom), 2010; Hou and Al-Tabbaa, 2014; Wang et al., 2022). The decision-making process for site remediation and land reuse using sustainable remediation approaches can consequently however be highly complex and subjective, because of inherent trade-offs between the environmental, social, economic and technical factors that influence the sustainability performance of contaminated site management (Kiker et al., 2005; Cundy et al., 2013; Naseri-Rad et al., 2022). This requires approaches and decision support methods that can effectively incorporate and consider these trade-offs in a holistic, reproducible, transparent (and ultimately defensible) manner.

Over the past few decades, a substantial amount of research has been conducted on decision support tools (DSTs) which allow selection of the

* Corresponding author.
E-mail addresses: xnli@rcees.ac.cn (X. Li), syyi_st@rcees.ac.cn (S. Yi), wpchen@rcees.ac.cn (W. Chen), A.Cundy@noc.soton.ac.uk (A.B. Cundy).

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most sustainable (in the view of site managers, operators or other stakeholders) management or remediation options for contaminated (and other regeneration) sites (Marcomini et al., 2009; Onwubuya et al., 2009; Rosén et al., 2015; Huysegoms and Cappuyns, 2017; Li et al., 2019). Accordingly, issues involving stakeholder involvement (Stezar et al., 2014; Braun et al., 2019; Prior and Rai, 2017), sustainability considerations or evaluation indicators (Cappuyns, 2016; Huysegoms et al., 2019; Li et al., 2021; Braun et al., 2021), and evaluation techniques (Ibáñez-Forés et al., 2014; Huysegoms et al., 2018; Søndergaard et al., 2018) have been widely discussed to facilitate the application of DSTs in sustainable site management practice. A range of techniques including Life Cycle Analysis (LCA), Multi-Criteria Decision Analysis (MCDA), and Cost Benefit Analysis (CBA) are recognized as potentially effective instruments in environmental decision making (Onwubuya et al., 2009; Song et al., 2018; Chen et al., 2020). However, a systematic methodology has yet to be fully developed for complex decision making, and some limitations of more traditional methodologies have been gradually found as time goes on, especially regarding the use of various types of data, available information and disputes between relevant stakeholders (Kiker et al., 2005).

In response to such challenges, MCDA is well suited to deal with complicated decision problems due to its capacity to integrate multi-attributive and multidimensional indices in a holistic manner to reach a more transparent and concise strategy (Rosén et al., 2015; Li et al., 2018; Villanueva et al., 2021; Murcia et al., 2022). Novel MCDA approaches based on health risk assessment (HRA), GIS, fuzzy set theory and other methods (e.g. TOPSIS and PROMETHEE) have been applied to demonstrate the most suitable management alternatives for contaminated soil and groundwater (Zheng, 2018; Fan et al., 2014; Li et al., 2012; Chen et al., 2021; Fernandes et al., 2021; Yang et al., 2012; Zheng et al., 2019), while the TOPSIS model (and modified versions of it) has been used across a range of sustainability-orientated decisional frameworks. The TOPSIS model has key advantages that it provides high computational efficiency (as a continuous model) and also has the ability to concurrently evaluate positive and negative "ideal" solutions and present these in a simple mathematical form (Hooshangi et al., 2023; Guo and Zhao, 2015; Xia et al., 2020; Balenzentis et al., 2021; Lin et al., 2022). It therefore offers advantages of providing a relatively simple and intuitive (and relatively easily communicated) approach when dealing with complex data.

Previous studies on contaminated soil and groundwater management have mainly focused on the sustainability performance of the particular remediation technology or management option applied, without considering the best management practices (BMPs) involved in the whole stepwise management process of site investigation, strategy design, remediation implementation, efficacy validation and land reuse. In addition, the specific index weighting methodology, which is a crucial component of a combined quantitative and qualitative analysis, is still debated in MCDA application. With the goal of addressing this gap, and providing a more rigorous assessment of sustainability performance across the whole contaminated site management process, a novel MCDA approach (with the specific contribution of evaluating contaminated site management (and its sustainability performance) from an extensive life cycle perspective) is developed here by establishing a combination weights-based TOPSIS model, with the rationale that this model type is substantially more resistant to uncertainty (in terms of indicator weighting) than a single subjective or objective weighting. This approach is then applied and tested on a range of existing contaminated sites in China. The study is organized as follows: Section 2 identifies the sustainability indices and relevant BMPs involved in subsequent evaluation, and introduces the MCDA methodology for sustainability ranking with a combination weights-based TOPSIS model. Section 3 presents a MCDA analysis of 11 contaminated sites in China and discusses recommendations for more sustainable management scenarios at these sites. Section 4 summarizes the study results and outlines the limitations to be addressed in future research.

2. Materials and methods

2.1. Evaluation framework

The method proposed by this study to evaluate the sustainability performance of contaminated site intervention measures consists of three steps, as shown in Fig. 1: firstly, the evaluation indices and BMPs are identified, and then the BMPs of selected sites are linked with relevant indices through a predefined relationship matrix (step 1). Secondly, a combination weighting method based on Social Network Analysis (SNA) and the DEMATEL-ANP Based Method (DANP) is created to determine accurate index weights (step 2). Thirdly, the sustainability scores are calculated and ranked by a TOPSIS model to identify the best decision for effective contaminated site management (step 3).

2.2. Evaluation index and relationship matrix

2.2.1. Identification of evaluation index

A qualified sustainable index system has been developed in previous work which defines sustainability based on four pillars, of environment, society, economy and technology. The system has been developed through two phases, firstly by collecting widely used indices internationally through a systematic bibliographic review (Li et al., 2021; Li et al., 2022). Then, considering that sustainability assessment is highly site specific, and (1) depends on opinions from a range of interested parties and stakeholders, and (2) sustainability drivers, context etc. can vary between different countries (Bardos, 2014), the initial identified indices were further adjusted and developed to comply with the practical implementation of contaminated site risk management in China, especially the principles of ecological civilization construction and policies executed for contaminated site management. The key difference between the approach used here and those of other (international) approaches involving sustainability indicators (e.g. SuRF) is the application of a fourth assessment pillar, that of technology (Hou, 2020; Ridsdale and Noble, 2016; Rizzo et al., 2016; Contaminated Land: Applications in Real Environments (CL:AIRE), 2011). While this risks double-counting of indicators (as the process of remediation option appraisal already incorporates the technical fit to risk management) this additional "technology" pillar has been included for the Chinese case studies used in this study as:

(1) Technology indicators are critical in selecting remediation technologies, and can directly influence social, environmental and economic indicators. Currently, China is in the initial stages of sustainable remediation practice, and technology indicators are readily applied and influence decision making and site remedial design, even prior to other indicators in many practical cases.
(2) The technology indicators applied are approved by a range of experts in China, following face to face discussions, are an important output of a National Key Project (grant number: 2020YFC1807500), and are included in existing Contaminated Site Sustainability Evaluation Software (registration number: 2022SR0549733).

2.2.2. Identification of BMPs

Best management practices (BMPs) are defined by ASTM as strategies incorporating green sustainable remediation (GSR) principles into remediation or management at a specific site to balance the key elements of sustainability, for instance, to reduce the concentration of existing pollutants as well as achieving significant social benefits (ASTM, 2020). BMPs are generally documented in project materials such as construction plans, and can be incorporated into all phases of site management (USEPA (U.S. Environmental Protection Agency), 2008). Therefore, BMPs can determine the implementation of GSR throughout the whole life-cycle process with likely influence on one or more sustainability indices. Furthermore, such causal interactions produce

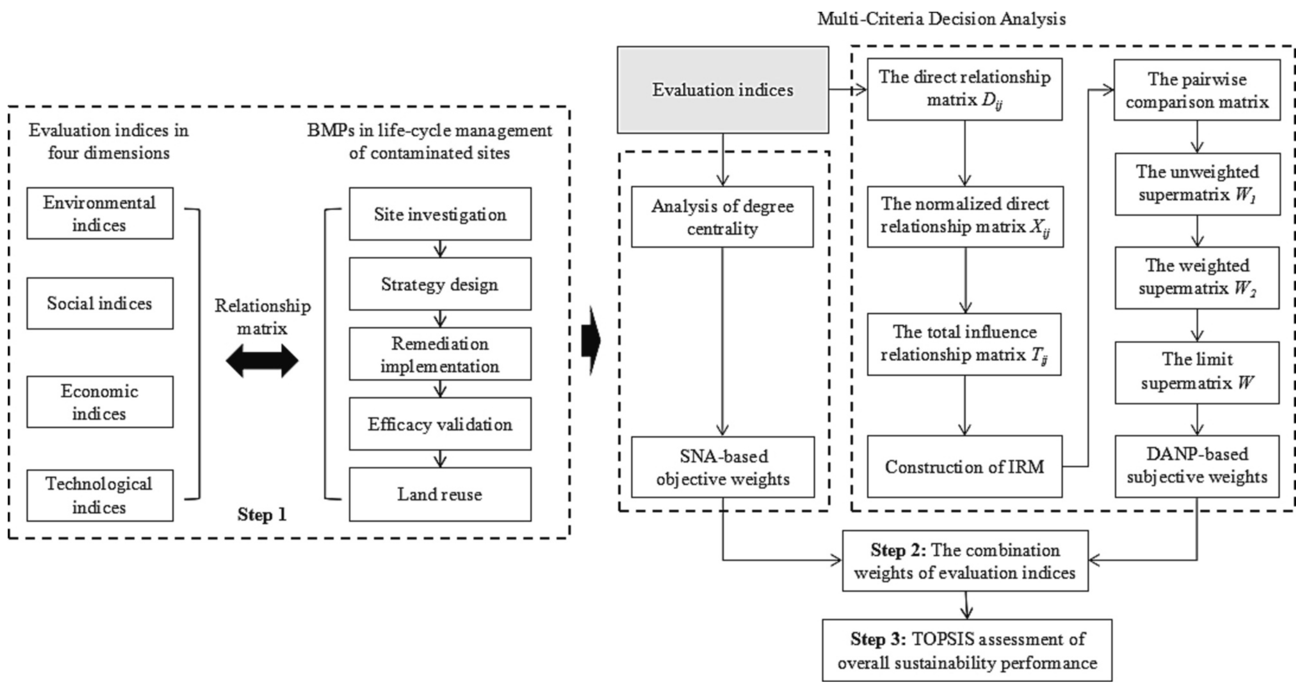


Fig. 1. Assessment framework for sustainable management of contaminated sites.

concrete relationships between specific BMPs and sustainability indices which may allow a quantitative evaluation to be performed.

The BMPs that might affect sustainability in the stepwise management processes of site investigation, strategy design, remediation implementation, efficacy validation and land reuse were identified via review of relevant published literature. Specifically, relevant literature was identified by searching "contaminated site" and "BMPs" in the Web of Science database; then, grey documents were added based on the research engine "Baidu" using the same key words. As a result, nine reports, guidelines, journal articles and books were screened for identification of 108 BMPs (ASTM, 2020; USEPA (U.S. Environmental Protection Agency), 1997, 2008; CAEPI (China Association of Environmental Protection Industry), 2020; Ellis and Hadley, 2009; ITRC (Interstate Technology and Regulatory Council), 2011; Gu et al., 2015; Hu et al., 2018; Bueno et al., 2021), which were considered to be potentially important in fostering green or sustainable remediation, including 16 BMPs at the site investigation phase, 30 BMPs at the strategy design phase, 40 BMPs at the remediation implementation phase, 11 BMPs at the efficacy validation phase and 11 BMPs at the land reuse phase, respectively. The 108 BMPs and their descriptions are shown in Supplementary material.

2.2.3. *Establishment of index-BMPs matrix*

The influences of BMPs on each index were assessed using a 0–1 scoring system referring to existing case outputs (mainly ASTM E 2893-13 Standard Guide for Greener Cleanups and relevant work reports) and experts' judgement ($n = 5$ in this initial scoring stage), in which, 1 means that the BMPs can affect the index directly or significantly while 0 means the influence is indirect or slight enough to be excluded. Based on all feedback, an Index-BMPs matrix was finally established in an Excel spreadsheet including 4758 cells to map the impacts on indices that might be delivered by BMPs, how they interact, and to what extent they interact.

Fig. 2 provides an overview of the relationship matrix used to describe the kind of sustainable aspects that each BMP might generate, and the synergies between a particular BMP and corresponding indices, where the horizontal axis represents 44 indices included in the four categories of environment, society, economy and technology, and the vertical axis shows 108 BMPs incorporated in 5 processes of site investigation, strategy design, remediation implementation, efficacy validation and land reuse. Strong interactions with a particular intervention are expressed with a score of 1, while marginal or no interaction is expressed with a 0 score. Taking the remediation implementation stage as an example, the intervention of wastewater treatment and reuse may have significant influence on 6 aspects, including avoidance of water pollution, reduction of fresh water consumption, adoption of reuse technology, compliance with regional policy goals, information disclosure on wastewater emission and investment in wastewater treatment. According to the 0–1 scoring system, the 6 indices are assigned with a 1 score to be converted to non-dimensional values. Similarly, the sustainability links of the other 107 BMPs can all be expressed by associated indices with a 1 or 0 score.

2.3. *Weighting approach*

The accuracy of evaluation results depends to a great extent on the selection of appropriate and effective weighting methods (Niu et al., 2022; Du and Gao, 2020). To reflect the characteristics of the indices' data and avoid subjective arbitrariness, a combined weighting method is proposed in this work to calculate optimal weights. Firstly, SNA was adopted to calculate objective weights, then, a DEMATEL-based ANP (Decision-Making Trial and Evaluation Laboratory) was applied to allocate subjective weights. Finally, both objective and subjective weights were integrated to create combination weights. The structure of the combination weighting method is shown in Fig. 1.

The detailed calculation processes are described below.

2.3.1. *SNA-based objective weighting method*

Based on graph theory, SNA, in conjunction with factor analysis, has been found to efficiently analyze key controlling variables and visualize interactions between nodes (evaluation indices) with the advantage of providing results with enhanced robustness (Bertoni et al., 2021; García-Lillo et al., 2023). Degree centrality is the most commonly used network analysis method to measure the influence of indices in a network, and a high degree centrality indicates a more influential position of an index (Kharanagh et al., 2020; Chuang et al., 2021). Hence, the standardized

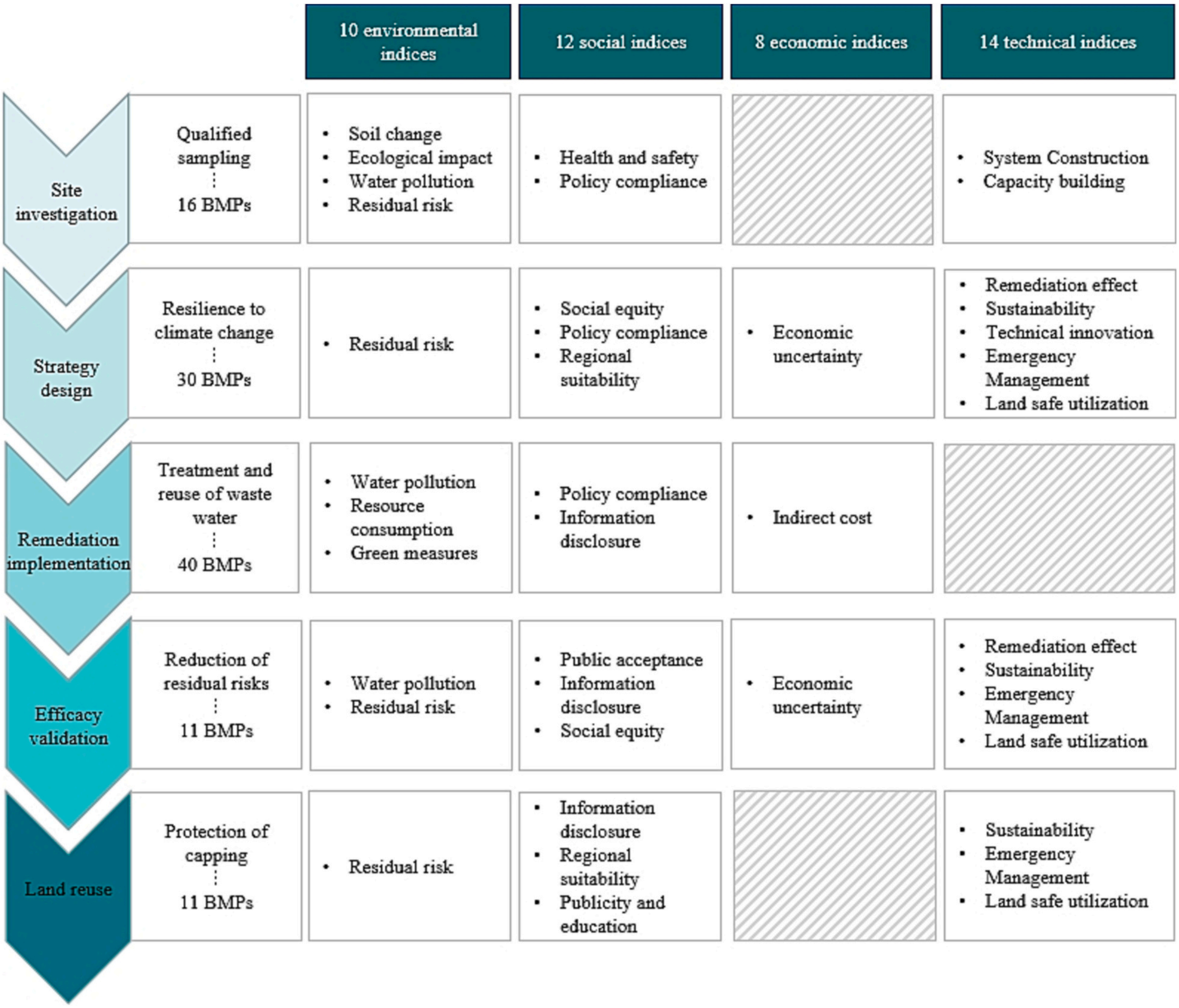


Fig. 2. Overview of the relationship matrix.

score of degree centrality (C_B) can be referred to the objective weight of a specific index (e.g. air pollution). The degree centrality for index i is calculated by Eq. (1) based on 93 publications previously gathered by Li et al. (2021).

$$C_B(n_i) = \sum_{j<k} g_{jk}(n_i)/g_{jk}; i \neq j \neq k \tag{1}$$

where, g_{jk} is the shortest path connecting n_j and n_k, and $g_{jk}(n_i)$ denotes the shortest path connecting n_j and n_k that passes through n_i. i, j and k represent different evaluation indices.

2.3.2. DANP-based subjective weighting method

DANP has been successfully applied to examine the prominent factors in multiple topics covering resource transformation, sustainability evaluation and environmental risks (Ekmekcioğlu et al., 2022; Guo et al., 2022; Rao, 2021). ANP can prioritize indices by calculating their weights based on pairwise comparison of various indices, however, in this manuscript, this would result in 1936 (44*44 indices) pairwise comparisons. Given the advantages that the DEMATEL method can not only detect causality and correlation between various indices, but also significantly reduce the scoring workload with only 16 (4*4 dimensions) pairwise comparisons, a hybrid DANP method was employed in this work to determine the subjective weights of evaluation indices. The calculation steps of the hybrid DANP method are as follows:

Step 1: Acquire a direct relationship matrix D_{ij}.

The degree of correlation between indices is expressed by a 5-point scale divided into 0 (no influence), 1 (low influence), 2 (moderate influence), 3 (high influence) and 4 (extremely high influence). K ($K = 20$ in this paper) experts are invited to score the direct relationship among indices, and $d_{ij}^{(K)}$ represents the degree of influence index i has on index j. Suppose there are n evaluation indices, then a n × n direct relationship matrix D_{ij} will be established with the average score of all experts. The diagonal elements in matrix D_{ij} are initially set to 0.

Step 2: Form a normalized direct relationship matrix X_{ij}.

Based on the direct relationship matrix D_{ij}, a normalized direct relationship matrix X_{ij} is produced via Eq. (2) and Eq. (3).

$$X_{ij} = \lambda \times D_{ij=} \lambda \times \left[d_{ij}\right]_{n\times n} \tag{2}$$

$$\lambda = min\left(\frac{1}{\max\limits_{1\leq i\leq n}\left(\sum_{j=1}^{n} d_{ij}\right)}, \frac{1}{\max\limits_{1\leq j\leq n}\left(\sum_{i=1}^{n} d_{ij}\right)}\right) \tag{3}$$

Step 3: Generate a total influence relationship matrix T_{ij}.

Based on the normalized relationship matrix X_{ij}, a total influence relationship matrix T is obtained via Eq. (4).

$$T = [t_{ij}]_{n\times n} = X(I-X)^{-1} \quad (4)$$

where, I represents the unit matrix, t_{ij} is the overall influence of index i on index j.

Step 4: Construct an Impact Relation Map (IRM).

Based on the total influence relationship matrix T_{ij}, r_i and c_j are obtained by summing the rows and columns of matrix T_{ij} via Eq. (5) and Eq. (6). Further, a $r_i + c_i$ value and $r_i - c_i$ value are calculated to be defined as the center degree and cause degree, respectively. The $r_i + c_i$ value reveals the total interaction intensity of index i with others while the $r_i - c_i$ value shows the likelihood that index i will influence other indices (Rao, 2021). To avoid interference relationships and identify key information for decision makers, the $r_i + c_i$ value and $r_i - c_i$ value are judged by a defined threshold value, and values exceeding the threshold are displayed in an IRM (Liu et al., 2021). With the $r_i + c_i$ value as a horizontal axis vector and the $r_i - c_i$ value as a vertical axis vector, the IRM is constructed to describe the important interrelationships among various indices.

$$r_i = \sum_{j=1}^{n} t_{ij} \quad (5)$$

$$c_j = \sum_{i=1}^{n} t_{ij} \quad (6)$$

Step 5: Calculate the subjective weights.

Based on the IRM constructed at step 4, to begin ANP calculation, a pairwise comparison matrix derived from an experts' questionnaire is firstly formed to express the relative importance of indices, which generally refers to a 9-grade scoring system defined by Saaty (2001). Subsequently, the unweighted supermatrix W_1, the weighted supermatrix W_2 and the limit supermatrix W are structured if the pairwise comparison matrix passes a consistency verification with $CR < 0.1$ (Wang et al., 2019). Considering that the calculation procedure is complicated and has been described in detail previously (e.g. Liu et al., 2021), this description is not repeated here. In this work, ANP is implemented using Super Decision Software V3.2 to calculate the subjective weights of the evaluation indices.

2.3.3. The combination weighting method

Combination weights of evaluation indices are calculated by integrating the objective weights with the subjective weights via Eq. (7) and Eq. (8).

$$\omega_i = \frac{\alpha_i\omega_{si} + \beta_i\omega_{oi}}{\sum_{i=1}^{n}\alpha_i\omega_{si} + \beta_i\omega_{oi}}, 1 \le \mathrm{i} \le n \quad (7)$$

$$\begin{cases} \alpha_i = \omega_{si}/(\omega_{si}+\omega_{oi}) \\ \beta_i = \omega_{oi}/(\omega_{si}+\omega_{oi}) \end{cases}, 1 \le \mathrm{i} \le n \quad (8)$$

where, ω_{oi} and ω_{si} express the objective weights and the subjective weights, respectively, and β_i and α_i are their relative importance coefficients.

2.4. TOPSIS model

TOPSIS is a popular method to determine the priorities of feasible alternatives for effective decision-making in multiple scenarios, including providing technical support for contaminated site remediation and sustainable management (Zhang et al., 2012; Luo, 2013; Wang et al., 2019; Li et al., 2021). In this study, the sustainability performance for contaminated site management is evaluated using TOPSIS, and the most sustainable site outcome is given top priority when it is closest to the positive ideal solution and farthest from the negative ideal solution. The calculation steps are as follows.

Step 1: Construct the initial matrix Y_{ij}.

Supposed there are n indices and m sites for evaluation, the raw indices' data constitute the initial matrix $Y_{ij} = [y_{ij}]_{n\times m}$, $(i = 1, 2, \ldots, m; j = 1, 2, \ldots, n)$.

Step 2: Normalize the dimensionless matrix Z_{ij}.

The dimensionless matrix Z_{ij} is constructed via Eq. (9), where z_{ij} represents the normalized value of y_{ij}.

$$Z_{ij} = [z_{ij}]_{n\times m} = \frac{Y_{ij}}{\sqrt{\sum_{i=1}^{m}(y_{ij})^2}} \quad (9)$$

Step 3: Obtain the weighted matrix D_{ij}.

The weighted matrix D_{ij} is processed via Eq. (10), where d_{ij} represents the weighted value of z_{ij} by multiplying each vector of the Z_{ij} with its corresponding combination weight calculated by Eq. (7).

$$D_{ij} = [d_{ij}]_{n\times m} = \omega_{i\times} [z_{ij}]_{n\times m} \quad (10)$$

Step 4: Determine the ideal solution.

The positive ideal solution and the negative ideal solution are calculated via Eq. (11) and Eq. (12).

$$D^+ = \max_{1\le i\le m} d_{ij} = \{D_1{}^+, D_2{}^+, \ldots, D_n{}^+\}, j = 1, 2, \ldots, n \quad (11)$$

$$D^- = \min_{1\le i\le m} d_{ij} = \{D_1{}^-, D_2{}^-, \ldots, D_n{}^-\}, j = 1, 2, \ldots, n \quad (12)$$

Step 5: Calculate the Euclidean distance.

The distance from column vector i to the positive or negative ideal solution is calculated via Eq. (13) and Eq. (14).

$$S_i{}^+ = \sqrt{\sum_{j=1}^{n}(d_{ij} - D_j{}^+)^2}, i = 1, 2, \ldots, m \quad (13)$$

$$S_i{}^- = \sqrt{\sum_{j=1}^{n}(d_{ij} - D_j{}^-)}, i = 1, 2, \ldots, m \quad (14)$$

Step 6: Calculate the relative closeness.

Closeness means the degree of a specific alternative complying with the ideal alternative. The alternative with higher closeness value gives the top priority for decision makers. The closeness of evaluation object i is calculated via Eq. (15).

$$V_i = \frac{S_i{}^-}{S_i{}^+ + S_i{}^-}, 0 \le V_i \le 1, i = 1, 2, \ldots, m \quad (15)$$

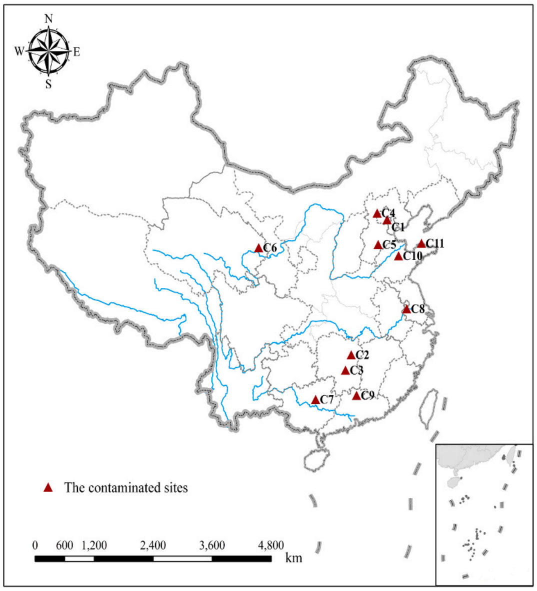
According to the overall value calculated by TOPSIS, the grade to which the sustainability performance of each site accords is defined in Table 1.

3. Applying and testing the approach: case studies

As shown in Fig. 3, 11 contaminated sites located in China were evaluated in this study, including the Dongfang Chemical Factory (C1), Changsha Chromium Salt Factory (C2), Hengyang Synthetic Medicine Factory (C3), Great Wall Chemical Factory (C4), Hebei Jiheng Co., Ltd. (C5), Huangzhong Xinfei Chemical Factory (C6), Lida Chemical Factory (C7), Nanjing Changfeng Agrochemical Factory (C8), Shaoguan Chemical Factory (C9), Shandong Dacheng Agrochemical Co., Ltd. (C10), and Penglai Chemical Factory (C11). Information included in site investigation reports, remediation designs and validation plans was collected through means of field investigation, online inquiry and stakeholder interviews ($n = 11$) to extract the raw data for subsequent quantitative evaluation.

Table 1
Five grades of evaluation values on sustainability performance.

Grade	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5
Description	Unsustainable level	Weak sustainability	Mid-less sustainable level	Medium sustainability	Strong sustainability
Value	0	(0, 0.25]	(0.25, 0.5]	(0.5, 0.75]	(0.75, 1]



Site	Time	Area or volume	Main contaminants of concern	Planned end-use	Technology
C1	2018-2026	900, 000 m^2 soil	Benzene, TPH and methyl tert butyl ether, etc.	Green space	Capping+Natural Attenuation+Institutional Control
C2	2019-2021	170, 000 m^2 soil	Chromium, zinc, arsenic and mercury, etc.	Green space, commercial land	Vertical Impermeable Wall+Landfill+Leaching+Stabilization+Long-term Monitoring+DGR(Dynamic Groundwater Recycle)+PRB (Permeable Reactive Barrier)
C3	2017.7-2017.11	3,423 m^2 soil	Cyanide, ethylbenzene, and styrene, etc.	Commercial land	Chemical Oxidation+PRB
C4	2020-2021	119, 000 m^2 soil and 427,088 m^2 groundwater	DDT and chlorinated hydrocarbon, etc.	No planning	Capping+Natural Attenuation+Institutional Control
C5	2017.6-2017.11	57, 351 m^2 soil and 11,159 m^2 groundwater	Ammonia-nitrogen	Recreational and commercial land	Thermal Desorption+Vertical Impermeable Wall+Pumping Treatment
C6	2018.11-2020.4	28,000 m^2	Cr^{6+}	Industrial land	Capping+Natural Attenuation+Institutional Control+Pumping Treatment
C7	2019.1-2019.5	35,245 m^3 soil	Arsenic and nickel	Commercial and residential land	Ex- site Landfill
C8	2018.11-2019.11	9,678 m^2 soil and 1,365 m^2groundwater	Benzopyrene and vinyl chloride, etc.	Green space and residential land	Chemical Oxidation+Thermal Desorption+Pumping Treatment+PRB
C9	2020.4-2020.11	83,068 m^2 soil	Arsenic and lead, etc.	School	Co-processing CementKiln+Vertical Impermeable Wall
C10	2019.3-2020.5	275,100 m^3 soil and 30,900m^3 groundwater	Benzene and trichloroethylene, etc.	Residential and educational land	Co-processing CementKiln+Chemical Oxidation+Thermal Desorption+Pumping Treatment+PRB
C11	2017.10-2018.4	35,096 m^3 soil and 6,950 m^2 groundwater	Nickel, cadmium, copper and toluene, etc.	Commercial and residential land	Stabilization+Thermal Desorption+Pumping Treatment

Fig. 3. Geographical location of, and general information on, sites evaluated in this study.

4. Results and discussion

4.1. Evaluation index system

Based on four pillars of sustainability - environment, society, economy, and technology, an index system referring to Li et al. (2021, 2022) is applied in this study to evaluate the sustainability performance of contaminated site management. As listed in Table 2, the four categories are divided into 44 indices with 10 in the environmental category, 12 in the social category, 8 in the economic category and 14 in the technical category. All indices have been previously proven to be critical factors that can potentially be influenced by site management activities, and consequently enable a comprehensive and robust evaluation for future decision making within the Chinese environmental and contaminated land context.

4.2. Combination weights of indices

Following the weighting methods proposed in subsection 2.3, the combination weights of evaluation indices were determined. Firstly, the objective weights of evaluation indices were calculated with Eq. (1) using data gathered from 93 publications (Li et al., 2021). Secondly, 20 experts were interviewed to create judgement matrices that were further processed to obtain subjective weights with Eq. (2) ~ (6). Finally, the combination weights were obtained with Eq. (7) ~ (8). The objective, subjective, and combination weights are shown in Fig. 4.

The combination weights reflect the objective characteristics of the literature data as well the subjective judgement of the experts consulted, and a greater weight implies a greater importance of the index in a sustainability analysis. In general, the importance of the four overarching categories during the life-cycle management of a contaminated site are ranked in descending order as environment (0.3866) > economy (0.2427) > technology (0.2139) > society (0.1568). The environmental category is given top priority due to mandatory regulations on secondary pollution prevention in China, while at the opposite end of this ranking, the social category has the lowest impact on sustainability performance, which may be explained by the reality that public engagement in the decision-making process of contaminated site management in China is frequently disregarded (Li et al., 2018). Economic and technical categories are almost of equal importance in terms of fostering sustainable management decisions. The implementation of feasible technologies, on one hand, is largely determined by economic factors, on the other hand, will directly affect the environmental footprint or impacts of a remediation project.

Of the 10 environmental indices, 5 indices including residual risk (EN10), greenhouse gas emissions (EN3), ecological impact (EN5), water pollution (EN6) and resource consumption (EN7) were assigned higher weights indicating the higher influence of each index (>10%) on environmental sustainability. Among these, EN 10 has the highest weight (0.0501), showing that site management actions primarily focus on the removal of existing pollutants rather than other adverse environmental impacts on air, ecology, water and resource caused by implementation of the remediation process. It is important to note the higher weight of soil change (EN4, 0.0368) indicating the significance of maintenance of soil function when undertaking remediation, i.e. limiting any detrimental impacts of the remediation or risk management processes on soil physical, chemical and biological properties (e.g. soil quality, structure and permeability).

Of the 12 social indices, health and safety (SO1) contributes the most significantly to social sustainability (22.45%) with the highest weight of 0.0352. This finding indicates that safety threats and health risks for site operators posed by direct exposure to pollutants are key factors used to measure social sustainability. Additionally, both public participation (SO4) and public acceptance (SO3) show strong influence on social sustainability with combination weights of 0.0189 and 0.0149, respectively. As a result, the sustainability performance of contaminated site management would be effectively improved by incorporating public perceptions and feedback in the whole decision-making process and

Table 2
Sustainable evaluation indices for contaminated site risk management.

Category	Index layer	Category	Index layer
Environment (EN)	Ecological restoration (EN1)	Economy (EC)	Direct cost (EC1)
	Air pollution (EN2)		Indirect cost (EC2)
	Greenhouse gas emissions (EN3)		Land value (EC3)
	Soil change (EN4)		Direct benefit (EC4)
	Ecological impact (EN5)		Indirect benefit (EC5)
	Water pollution (EN6)		Environmental protection investment (EC6)
	Resource consumption (EN7)		Investment and financing innovation (EC7)
	Waste generation (EN8)		Economic uncertainty (EC8)
	Green measures (EN9)	Technology (TE)	Remediation time (TE1)
	Residual risk (EN10)		Remediation effect (TE2)
Society (SO)	Health and safety (SO1)		Sustainability (TE3)
	Community disturbance (SO2)		Remediation position (TE4)
	Public acceptance (SO3)		Technical innovation (TE5)
	Public participation (SO4)		Technical availability (TE6)
	Information disclosure (SO5)		Technical maturity (TE7)
	Social equity (SO6)		Technical feasibility (TE8)
	Policy compliance (SO7)		Technical operability (TE9)
	Regional suitability (SO8)		Emergency management (TE10)
	Employment opportunities (SO9)		Directory management (TE11)
	Ecological culture (SO10)		Land safe utilization (TE12)
	Examine index (SO11)		System construction (TE13)
	Publicity and education (SO12)		Capacity building (TE14)

coordinating conflicts between different stakeholders. Considering the special demands on ecological civilization construction in China, the "examine" index (SO11, which refers to performance appraisal by the government on site and project managers) is strongly defined in our sustainability evaluation showing a weight (0.0127) higher than the average value. With the increasing inclusion of soil pollution prevention and control into government performance appraisal, SO11 is expected to continuously contribute to social sustainability. The lowest influence is achieved by information disclosure (SO5, with the lowest weight of 0.0026), flagging its current status as the most inefficient index in terms of overall sustainability, and indicating that more focus should be given in future management approaches to public information disclosure and dissemination.

Of the 8 economic indices, the combination weights imply that direct cost (EC1, 0.0460) is the most important element in the economic dimension, together with environmental protection investment (EC6), investment and financing innovation (EC7), land value (EC3) and economic uncertainty (EC8) - their contribution to economic sustainability is as high as 72.22%. Recently, innovative approaches for investment and financing including PPP models, green finance and bond issuance have been encouraged and tested in more and more remediation projects in China to cope with the huge financial pressure and liabilities in large, complex projects. Another important aspect of economic sustainability is the value-added potential of the site and surrounding land after soil remediation, which calls for multi-functional land providing housing, green space and business, etc. Indirect cost (EC2) has the lowest priority (lowest weight of 0.0191), presumably as the difficulty in quantifying EC2 in monetary terms leads to its limited role in influencing economic sustainability, for instance, health damage cost caused by exposure to contaminants.

Of the 14 technical indices, remediation time (TE1) and remediation effect (TE2) are the top two indices ranked with importance >11.40%. This can be explained by the fact that decisions made for sustainable site management depend strongly on remediation duration and risk elimination (or, more achievably, risk minimization). Technical performance-related indices including technical innovation (TE5), technical availability (TE6), technical maturity (TE7) and technical operability (TE9) are also important, with a combined contribution of 29.09%. It appears that four new indices established based on regional policies including directory management (TE11), capacity building (TE14), land safe utilization (TE12) and system construction (TE13) have a potential ability to improve technical sustainability with influence levels ranging from 5.53% to 8.05%. In comparison, technical sustainability is less affected by remediation position (TE4, referring to where remediation takes place – on-site or off-site, in-situ or ex-situ), for which the combination weight (0.0074) is considerably lower than the average value (0.0153). However, in-situ remediation is being given increasing emphasis and support in China over ex-situ remediation because the latter may pose relatively high secondary pollution risk, and moreover may require more economic input.

4.3. Sustainability performance

With respect to the TOPSIS evaluation results calculated using Eq. (9) ~ (15), the sustainability of the risk management approaches applied in 11 sites varies widely (Fig. 5). C1 and C4 rank most highly (Grade 5), with values of 0.9345 and 0.8219 indicating strong sustainability status/performance. The risk management measures applied at these two sites have several advantages including eliminating secondary pollution, reducing cleanup cost and shortening direct treatment duration. In contrast, C3, C5, C6, C8 and C10 rank at the mid-less sustainable level (Grade 3) with values of 0.4839, 0.3534, 0.4364, 0.4516 and 0.4143, respectively. Their relatively poor performance (in terms of sustainability) might be explained by: (1) most of these cleanup projects began before 2019, when awareness of green and sustainable remediation in China was still underdeveloped; (2) these projects show strong disturbance of the local environment due to combined soil and water remediation, the presence of a range of sensitive receptors and high social concern, which resulted in a lower-than-expected performance in terms of environmental, social, economic and technical sustainability.

4.3.1. Analysis of BMPs implementation

The average number of BMPs implemented in the whole life-cycle management of contaminated sites is 76 out of 108. As shown in Fig. 5, C1 is listed as the site with the most BMPs (94), whereas C6 shows the lowest number (59 BMPs). Seven BMPs are applied at all sites (i.e. with an executive ability of 100% (where executive ability is the percentage of sites implementing a BMP compared to all 11 sites)), while 12 BMPs are poorly applied with executive ability ranging from 2.27% to 54.55% (average 29.55%) (Table 3). In particular, energy saving and emission reduction, local resource input, and technological innovation and transformation are all factors in urgent need of improvement.

4.3.2. Analysis of importance of evaluation indices

In Fig. 6, the horizontal axis represents 44 evaluation indices and the vertical axis represents the 11 case study sites. Fig. 6 (a), (b), (c), and (d) demonstrate the sustainability performance in environmental, social, economic and technical dimensions, respectively. The indices' values range from 0.0112 to 1.1270 (average 0.38), indicating that the contributions of 44 indices to the overall sustainability of the 11 sites are

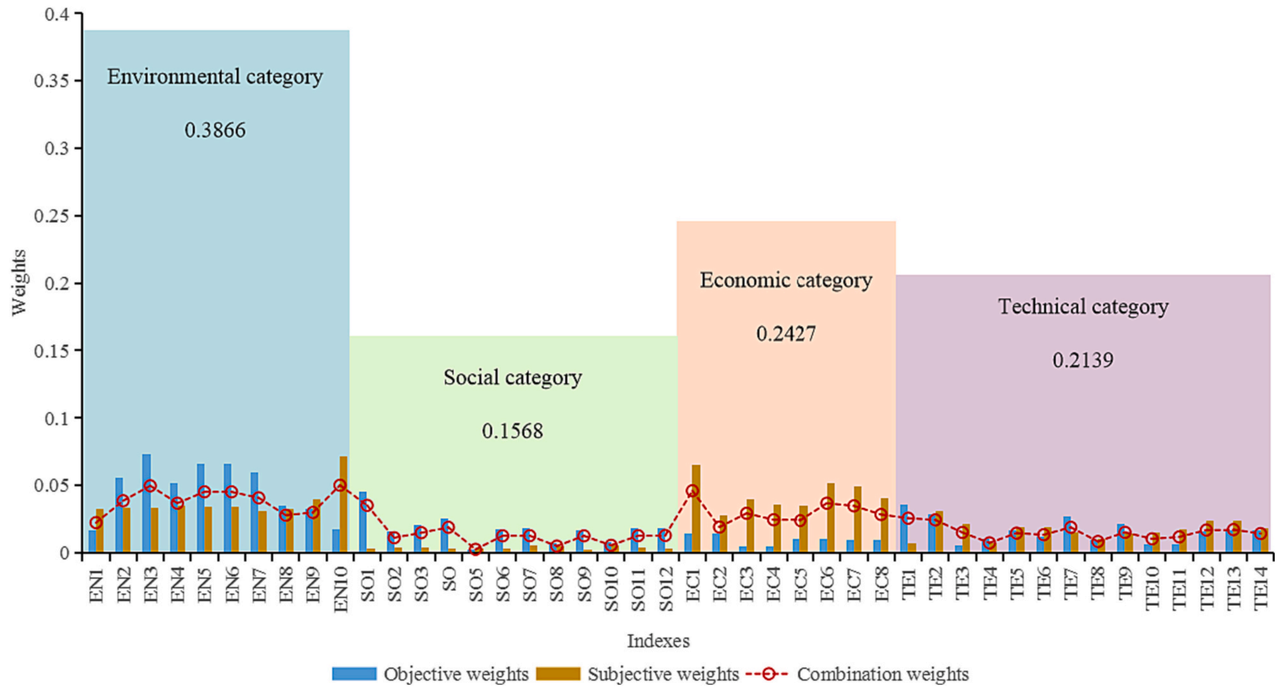


Fig. 4. Index weights for sustainability evaluation. See Table 2 for Index abbreviations (x-axis).

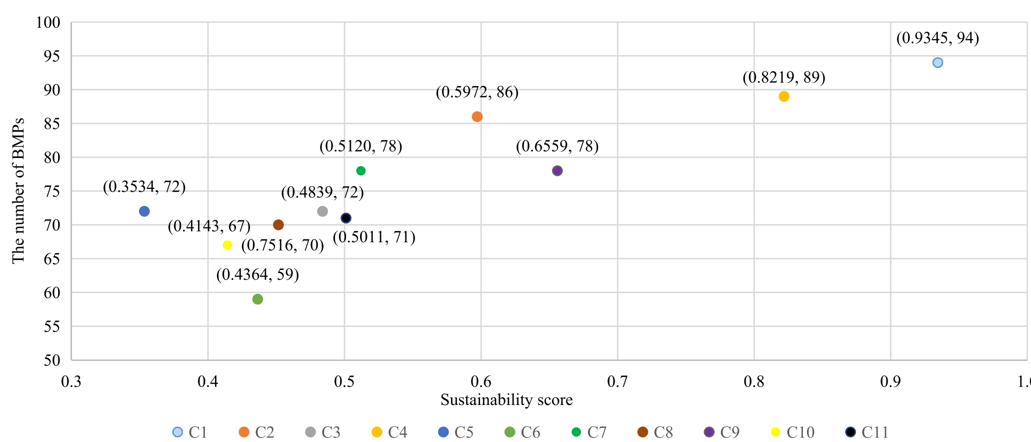


Fig. 5. The overall sustainability performance of 11 sites.

significantly different. The four most important indices are EC1, EN6, EN10 and EN3 with an average driving influence of 0.9264 (max. 1.1270), followed by EN2, EN7, TE2, SO1, EC8, EC5 and SO7 with an average contribution of 0.6422 (max. 0.8106). In comparison, SO10, SO9, TE4 and SO5 have the weakest impact on the sustainable performance of site management, with an average level as low as 0.0608 (min. 0.0112). As for the assessment indices, the higher the index value, the more important it is for priority consideration in engineering practices, whereas a lower index value highlights areas requiring further emphasis or development.

4.3.3. *Analysis of the life-cycle process*

The top right figure in Fig. 7 shows the relationship of sustainability score between different dimensions (horizontal and vertical axis) in each process (dots in different colors). There is a positive linear correlation between the four dimensions of environment (EN), society (SO), economy (EC) and technology (TE). Among these, EN has the best sustainability performance across the whole life cycle of site management, whereas the sustainability performance of SO is the lowest. The average sustainability performance of each dimension sorted by TOPSIS values in descending order is EN (0.0860) > TE (0.0286) ≈ EC (0.0277) > SO (0.0188), indicating that environmental sustainability is the primary current focus of site risk management (from a sustainability perspective), with social sustainability currently under-emphasised.

The bottom left figure in Fig. 7 shows the sustainability score (vertical axis) of each dimension (horizontal axis) for each process (curves in different colors). In terms of the life cycle process, the average sustainability performance of each management phase is sorted by TOPSIS values in descending order as P2 (0.0812) > P3 (0.0678) > P1 (0.0253) > P4 (0.0167) > P5 (0.0104). The sustainability levels of the strategy design phase (P2) and the remediation implementation phase (P3) in each dimension are much higher than that of the site investigation phase (P1), the efficacy validation phase (P4) and the land reuse phase (P5), indicating that the sustainability of site management is currently largely determined by decisions and actions taken in P2 and P3. On the other hand, P4 and P5 impede the sustainability of decision making over the whole life-cycle process, and should be given more focus (and their sustainability performance improved) in the future.

Table 3
The BMPs employed in life-cycle management of contaminated sites.

BMPs	Executive ability (%)	BMPs	Executive ability (%)
Avoidance of damaging and disturbing soil structure	48.48	• Corresponding qualifications for companies and technicians • Observing sample storage and transfer requirements • Multi-department coordination and supervision to ensure safe land reuse • Personnel protection and safety measures • Secondary pollution prevention and control • Scientific and rational design of remediation plan • Cleanup sites considering the local conditions	100
Energy saving and emission reduction	2.27		
Reduction of secondary pollution	22.73		
Technological innovation and transformation	13.64		
Consideration of financial risk	27.27		
Lab scale and pilot scale of technology	36.36		
Public participation and social equity	25.00		
Local resource input	9.09		
Measures on project schedule guarantee	33.33		
Reservation of land ecological service function	36.36		
Improvement of regional economic development	54.55		
Compliance with regional development planning	45.45		

4.4. Sensitivity analysis

Considering that data used in MCDA are commonly changeable (e.g. depending on data availability, selection of experts for qualitative assessments etc.), sensitivity analysis is an essential step to discover how uncertainty in the output of a model responds to variation of the input parameters (Simanaviciene and Ustinovichius, 2010). In this study, a Monte Carlo method is applied to perform sensitivity analysis on the TOPSIS model using 500 iterations to randomly generate initial weights of 44 indices, based on the hypothesis that the total sum of all weights must be equal to 1.

Fig.8 presents the sensitivity of 11 sites' sustainability score to the variation of indices' weights. The more likely sustainability grade that each site is given shows no difference (through 500 iterations) with the evaluation result in this study. For example, the probability that C1 falls in Grade 5 (with score ranging from 0.75 to 1) is much greater (90.4%) than for other grades (9.6%). The ranks of the 11 sites' sustainability performance are consistent up to 94%, among which, C1 is observed to be more sensitive to indices' weights compared to other sites with a score ranging from 0.7202 to 0.9711. The results indicate that random variations of the weights applied do not result in significant alteration of the final results (or grades), and the TOPSIS method for the chosen problem in our study is relatively robust and effective. The sensitivity of TOPSIS-related approaches has also been examined across various disciplines in previous studies, with similar results (Hasanzadeh et al., 2023; Simanaviciene and Ustinovichius, 2010; Bhadra et al., 2022; Dewangan et al., 2015).

4.5. Advantages and limitations

Decisions made for contaminated site management are site-specific and subject to complex multifaceted conditions. The improved TOPSIS model in this study provides a life-cycle insight into sustainability mechanisms, and a holistic quantitative method incorporating more robust data from social, environmental, economic and technical

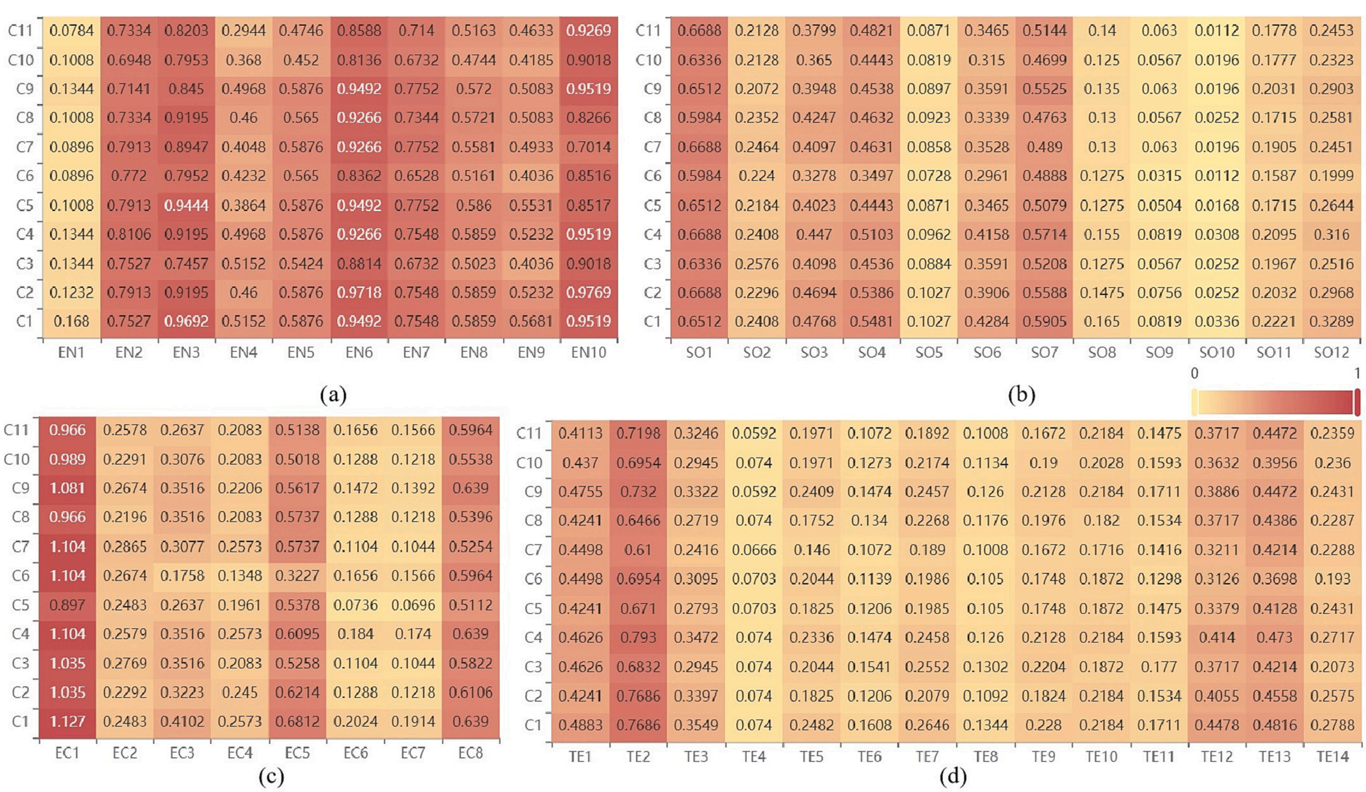


Fig. 6. Heatmap of index importance on overall sustainability.

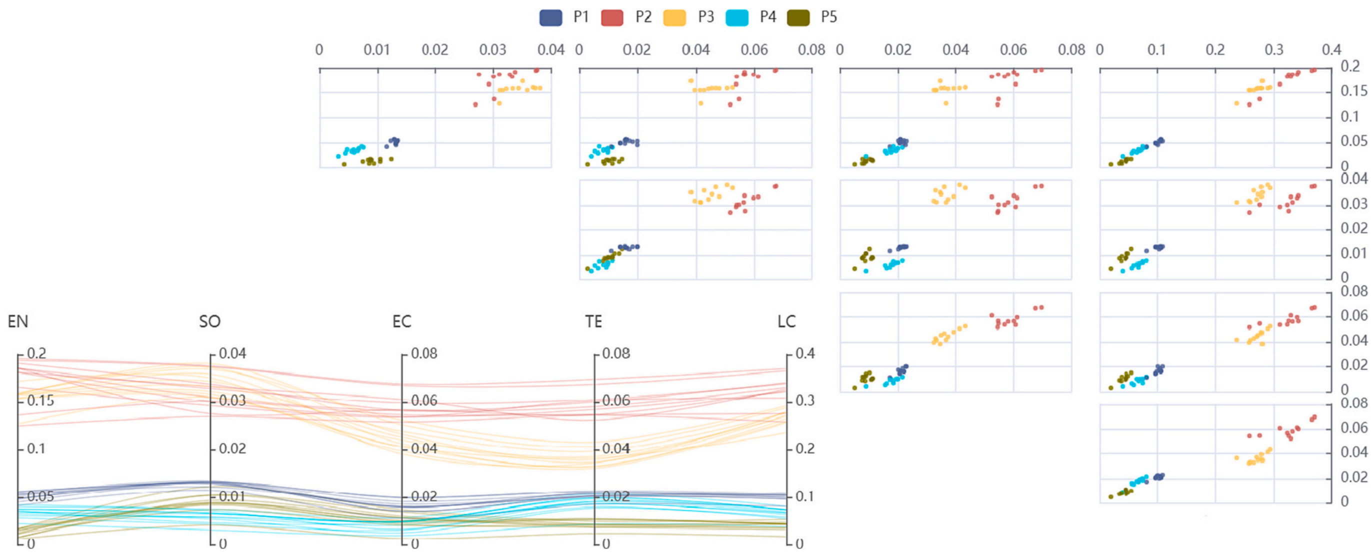


Fig. 7. Scatter matrix of correlation over the life-cycle process with sustainable dimensions.

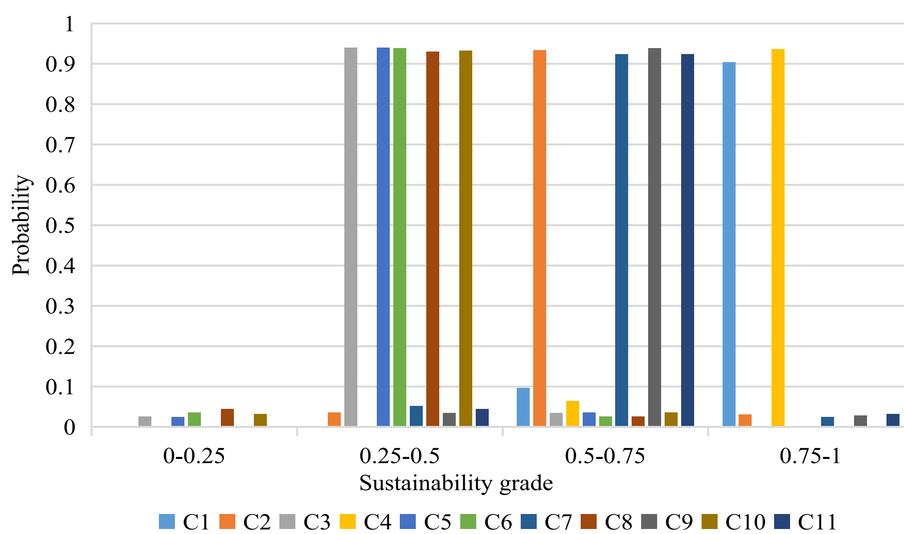


Fig. 8. Ranking scores of 11 contaminated sites with induced disturbance of the combination weights.

perspectives. The results of sensitivity analysis show that the combination weight-based TOPSIS approach is robust to random variations of indices' weights, which indicates that it should provide a relatively reliable result for effective decision making in contaminated site management.

Several limitations however need to be addressed in further research to help policy makers and executives more effectively identify key strengths and weaknesses in contaminated site management and its sustainability benefits (or disbenefits). Firstly, the links between BMPs and the evaluation indices presented in the Index-BMPs matrix are subjective, and can only be reliably ascertained by interview with more experienced site stakeholders (e.g. managers, experts and technicians). Secondly, the entire time span of risk management could be several years to decades, and the information required for indexing data may be difficult to track and collect over such a sustained period, generating time-consuming and high staff / research inputs for prospective evaluation, rather than for the retrospective evaluation applied here. Thirdly, the model and indicators used here are developed from the cultural, technical and economic background of the Chinese contaminated land sector, and so further work is needed to determine the transferability of the model and indicators to other national situations, and align it with other ongoing international work on sustainability assessment, indicators and performance in contaminated land risk management.

5. Conclusions

The present study systematically investigates the factors that can influence the sustainability performance of contaminated site life-cycle management using an improved TOPSIS model based on a combination weights method. The main conclusions are:

(1) The sustainability performance across the various sites highlights significant inter-site differences, with two sites showing strong sustainability performance, but five sites ranking at the mid-less sustainable performance level;
(2) 12 poorly executed BMPs, especially energy saving and emission reduction, local resource input, and technological innovation and transformation, have been highlighted as areas for improvement in future site remediation and management projects;
(3) Sustainability on an environmental level performs most strongly, while social aspects are least emphasised currently. Across the four dimensions assessed here, direct cost, water pollution,

residual risk and greenhouse gas emissions have the greatest influence on sustainability performance, by contrast, ecological culture, employment opportunities, remediation position and information disclosure have capacity to be further developed;
(4) The strategy design and remediation implementation phases play a vital role in sustainability performance of contaminated site life-cycle management, whereas the efficacy validation and land reuse phases have yet to be given sufficient importance;
(5) The combination weight-based TOPSIS model has been found to be a reliable MCDA technique that enables stakeholders to adopt optimal BMPs for risk control in contaminated site management. Future work should focus on the identification of indices, links between BMPs and indices, and data acquisition techniques for an extended application at a global scale.

CRediT authorship contribution statement

Xiaonuo Li: Investigation, Conceptualization, Visualization, Writing – original draft, Writing – review & editing, Funding acquisition. **Shiyi Yi:** Formal analysis. **Weiping Chen:** Writing – review & editing, Supervision. **Andrew B. Cundy:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eiar.2023.107327.

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