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From Plot-Level Technology Screening to Multi-Plot Remediation Decision-Making in Contaminated Industrial Parks: A Preference-Guided Multi-Objective Framework

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Abstract

Soil and groundwater contamination across multiple plots in industrial parks is an important environmental management challenge. Because plots often differ in contamination characteristics and remediation requirements, remediation decision-making needs to generate sustainability-oriented alternatives that account for explicit management preferences and trade-offs among carbon emissions, remediation duration, and cost. Although technology screening for individual contaminated plots has been widely investigated, how to use plot-level screening results to support the selection of multi-plot remediation alternatives under multiple objectives remains insufficiently addressed. This study developed a preference-guided multi-objective decision framework for selecting remediation alternatives in contaminated industrial parks. The framework first generates cross-plot remediation alternatives by assigning one feasible technology to each plot and removes alternatives that violate technological compatibility or project-level engineering constraints. It then identifies Pareto non-dominated alternatives using NSGA-II, retains preference-consistent alternatives through LO-based filtering, and selects the final recommendation using ideal-point distance comparison. The framework was applied to a five-plot contaminated industrial park in northern China. Compared with the LO and NSGA-II benchmarks, the hybrid NSGA-II-LO model selected less imbalanced alternatives that retained the preferred-objective advantage while improving the balance among the remaining objectives. The results show that management priorities can substantially affect remediation technology allocation across plots and that preference screening can support the adjustment of remediation alternatives when low-carbon targets, remediation schedules, or budget constraints change. This study provides an operational decision framework for translating plot-level technology screening into sustainability-oriented multi-plot remediation decision-making.



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1. Introduction

Industrial parks are designated areas in which multiple enterprises are spatially concentrated under unified planning [1]. Around 20,000 industrial parks have been established

worldwide, and many have subsequently been shut down or relocated during urban renewal and industrial restructuring [2]. This process has left large areas of legacy industrial land with complex soil and groundwater contamination problems [3,4]. Such soil and groundwater contamination poses risks to ecosystems and public health and can delay subsequent land redevelopment [5–7]. Unlike isolated contaminated sites, contaminated industrial parks often contain multiple adjacent contaminated plots with different contaminant types, contamination levels, hydrogeological conditions, and remediation requirements [3,8–10]. At the same time, green and sustainable remediation has increasingly emphasized cleaner remediation practices that reduce environmental burdens while remaining technically and economically feasible [11,12]. Therefore, remediation decision-making for contaminated industrial parks should go beyond contaminant removal by coordinating technology selection across multiple plots and jointly accounting for carbon emissions, remediation duration, and cost [9,13].

For individual contaminated sites, sustainability-oriented technology screening has been extensively investigated using decision-support methods and tools, including multi-criteria decision analysis (MCDA) [14], life cycle assessment (LCA) [15], cost–benefit analysis [16], risk-based decision-support tools [17], and technology-screening matrices such as the Technology Screening Matrix [18]. These approaches have provided an important basis for selecting technically feasible and environmentally sound remediation options under individual site conditions [19]. However, plot-level technology screening alone cannot determine a park-level remediation alternative for a contaminated industrial park after zoning. In plot-level decision-making, the main task is usually to identify the most suitable technology for an individual plot [20], whereas in an industrial park the decision target is to coordinate technology choices across multiple plots and form an overall park-level alternative [21]. Because applying the same or coupled technologies to adjacent plots may generate environmental, economic, and schedule-related synergies through shared infrastructure, equipment mobilization, centralized treatment, and scale effects [22–24]. Therefore, extending plot-level screening results to park-level remediation decision-making requires a framework that can coordinate both single and combined technologies across multiple contaminated plots.

Existing studies commonly divide contaminated areas into spatially distinct plots for remediation based on contaminant types and contamination levels [25]. Recent studies have further extended zoning-based remediation decision-making. For example, Zhao et al. [26] developed a framework that combines contamination grading and zoning with intelligent remediation technology selection for heavy-metal-contaminated sites, and applied it to 85 remediation zones in a large lead–zinc smelting site. Although their study demonstrates the need for differentiated technology selection after zoning, it still needs to cover broader site types, contaminants, and remediation technologies [26], while being further extended from zone-level technology selection to park-level remediation decision making. In related multi-plot remediation studies, applicable technologies are generally identified for each plot, and a limited number of cross-plot remediation alternatives are then predefined as scenarios for comparison using LCA [9], GIS-based spatial evaluation [21], or integrated decision-support and assessment models [8,17]. Although useful in practice, this paradigm can become inefficient when many plot-specific technology options need to be considered. More broadly, optimization-based methods can complement scenario comparison by generating and evaluating alternatives beyond the predefined set [27]. Therefore, an efficient decision framework is needed to extend single-plot technology screening to multi-plot optimization of remediation technology combinations in contaminated industrial parks.

Multi-objective optimization (MOO) can support this extension by exploring large sets of cross-plot technology combinations while considering conflicting objectives [22,28].

Recent MOO studies have shown clear benefits for remediation decision-making across different spatial scales. Jin et al. [28] optimized land-use planning and remediation strategies for a large contaminated site, reducing remediation volume by 62.5% and cost by 28.3% while increasing land-use benefits by 24.3%. At a broader city scale, Song et al. [22] integrated MOO with life-cycle sustainability assessment to compare centralized and decentralized remediation strategies for 286 contaminated sites, reporting reductions in environmental impacts and life-cycle costs. These studies demonstrate the potential of MOO for remediation decision-making, but the selection of plot-specific remediation technology combinations from large solution sets under management preferences remains insufficiently addressed.

Among available methods, non-dominated sorting genetic algorithm II (NSGA-II) is a representative evolutionary algorithm for MOO [29]. It can explore trade-offs among carbon emissions, remediation duration, and cost and generate a Pareto set representing alternative compromise solutions [30]. However, NSGA-II does not itself incorporate management preferences [31]. When managers place different priorities on low-carbon performance, schedule compression, or cost control, the resulting Pareto set may still contain redundant alternatives and be difficult to translate into a final engineering decision [32]. Lexicographic optimization (LO) provides a complementary preference logic because solutions can be screened according to a predefined priority order and screening ratio, thereby preserving the advantage of the preferred objective while leaving room for secondary-objective improvement [33]. Used alone, however, LO is sensitive to the predefined priority order and screening ratio, which may make the search dependent on a specific preference path rather than comprehensively exploring the full multi-plot combination space [34,35]. Therefore, combining NSGA-II with an LO-based screening rule can link Pareto set generation with preference screening.

This study proposes a preference-guided multi-objective decision framework that supports sustainable remediation decision making across multiple plots in contaminated industrial parks by connecting plot-level technology screening with the generation, evaluation, and selection of multi-plot remediation alternatives. The framework screens feasible technologies for each plot, generates cross-plot alternatives, incorporates technological compatibility constraints, project-level engineering constraints, and cross-plot synergy adjustments, and then uses NSGA-II, LO-based preference filtering, and ideal-point distance comparison to recommend alternatives under carbon-first, duration-first, and cost-first scenarios. The framework was applied to a contaminated industrial park in northern China. The aims were to: (1) link plot-level technology screening to the generation and multi-objective evaluation of multi-plot remediation alternatives; (2) identify recommended alternatives from a large set of candidate alternatives under different management preferences; and (3) examine how preference-screening results can support the adjustment of remediation alternatives when carbon, schedule, or budget requirements change.

2. Materials and Methods

2.1. Decision-Support Framework

The preference-guided decision framework for multi-plot soil and groundwater remediation in contaminated industrial parks consists of five steps. First, the contaminated area is divided into plots according to contamination characteristics and remediation requirements. Second, feasible remediation technologies are screened for each plot, and a parameter database is compiled for carbon emissions, remediation duration, and cost. Third, plot-specific technologies are combined to generate candidate multi-plot remediation alternatives, and the objective values of each alternative are calculated after cross-plot synergy adjustments. Fourth, only alternatives satisfying both technological and engineering

constraints are retained. Finally, within this framework, the final alternative selection is implemented using an NSGA-II–LO preference-guided selection procedure, which combines NSGA-II for Pareto search, LO for preference filtering, and ideal-point distance comparison for final recommendation. LO and NSGA-II are also applied separately as benchmark procedures. In this framework, the sustainability-oriented assessment is operationalized through the three planning objectives: carbon emissions, remediation duration, and cost.

2.2. Study Area and Plot Delineation

The study area is a contaminated industrial park in Tianjin, China (Figure 1a–c). It was historically occupied by food-processing, machinery-manufacturing, and electronics enterprises. Due to early unregulated production practices and subsequent enterprise relocation, both soil and groundwater were affected by organic contamination. The main contaminants of concern were chlorinated volatile organic compounds, including perchloroethylene, trichloroethylene, vinyl chloride, and *cis*-1,2-dichloroethylene, as well as ethylbenzene and total petroleum hydrocarbons. The planned land use includes green space and commercial service facilities above ground and metro construction underground. Therefore, remediation target values were set to meet Category I land-use standards under the *Soil Environmental Quality Risk Control Standard for Soil Contamination of Development Land* [36].

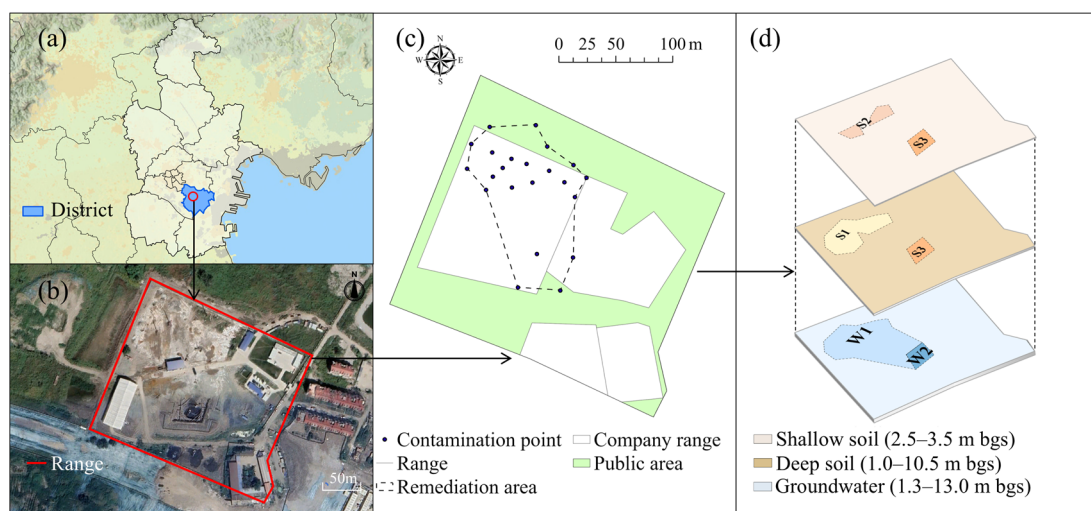


Figure 1. Location (a–c) and contamination distribution (d) of the study area.

The contaminated area in the industrial park was divided into five plots according to contaminant type, contamination level, and affected medium, including three soil plots (S1, S2, and S3) and two groundwater plots (W1 and W2) (Figure 1d and Table 1). S1 and W1 had relatively large contaminated volumes and were mainly affected by low-to-medium concentrations of chlorinated volatile organic compounds (CVOCs). S3 represented a heavily contaminated plot at the former core production workshop. Although S3 accounted for only 2.4% of the total remediation volume considered in this study, the maximum contaminant concentration in this plot was approximately 98.2 times the corresponding remediation target value.

Table 1. Overview of contaminated plots in the study area.

Plot	Characteristics	Remediation Depth (m bgs) ¹	Remediation Volume (m ³)	Contaminants of Concern ²
S1	Lightly contaminated soil with low-chlorinated hydrocarbons	1.0–10.5	26,567.45	VC
S2	Lightly contaminated soil with high-chlorinated hydrocarbons	2.5–3.5	4340.35	VC, TCE, EB
S3	Heavily contaminated soil	0.4–7.6	8328.80	VC, <i>cis</i> -1,2-DCE, TCE, PCE
W1	Lightly contaminated groundwater	1.3–13.0	286,554.84	VC, TCE
W2	Heavily contaminated groundwater	1.3–13.0	14,887.73	VC, <i>cis</i> -1,2-DCE, TPH, TCE

¹ m bgs = meters below ground surface. ² VC = vinyl chloride; TCE = trichloroethylene; EB = ethylbenzene; *cis*-1,2-DCE = *cis*-1,2-dichloroethylene; PCE = perchloroethylene; TPH = total petroleum hydrocarbons.

2.3. Plot-Level Technology Screening and Parameter Database

A plot-level screening procedure was used to construct the feasible technology set. For each contaminated plot, candidate technologies were first screened according to contaminant characteristics and subsurface media conditions, including soil texture and aquifer medium type. The retained technologies were then assessed for engineering applicability. This assessment considered plot applicability, technical performance, and environmental impact. The assessment results were used to form the feasible technology set for each plot (Text S1, Tables S1–S7, Figure S1).

For each feasible technology, a parameter database was compiled for carbon emissions, remediation duration, and cost using engineering cases, published literature, industry guidelines, laboratory tests, and pilot-scale data (Text S2, Tables S8 and S9). Cross-plot synergy parameters were also incorporated into the database for remediation combinations in which identical or coupled technologies were applied to multiple plots. These synergies represented possible reductions in carbon emissions, remediation duration, and cost due to shared infrastructure, equipment mobilization, centralized treatment, and scale effects (Text S3, Table S10). Detailed parameter sources, derivations, and synergy-adjustment assumptions are provided in Texts S2 and S3 and Tables S8–S10 in the Supplementary Materials.

2.4. Generation and Assessment of Multi-Plot Remediation Alternatives

2.4.1. Generation of Remediation Combinations

Each multi-plot remediation alternative is represented by a remediation combination consisting of one feasible remediation technology for each contaminated plot. A candidate remediation combination can therefore be written as Equation (1):

$$x_k = (x_{1k}, x_{2k}, \dots, x_{jk}), x_{jk} \in T_j \quad (1)$$

where x_k denotes the k th remediation combination, and x_{jk} is the technology selected from the feasible technology set T_j for plot j .

The total number of candidate combinations is given by Equation (2):

$$N = \prod_{j=1}^J |T_j| \quad (2)$$

where N is the size of the candidate combination set, J is the number of contaminated plots, and $|T_j|$ is the number of feasible technologies for plot j .

2.4.2. Objective Assessment and Synergy Adjustment

Each remediation combination was assessed against three minimization objectives: carbon emissions, remediation duration, and cost. After cross-plot synergy adjustment, the aggregate value of each objective was calculated as Equation (3):

$$F_{m,k} = \sum_{j=1}^J v_{m,j,k} - \Delta_{m,k} \quad (3)$$

where $F_{m,k}$ is the value of objective m for remediation combination k , $v_{m,j,k}$ is the plot-level parameter value for objective m associated with the technology selected for plot j , and $\Delta_{m,k}$ is the cross-plot synergy deduction. Lower $F_{m,k}$ values indicate better performance for carbon emissions, remediation duration, and cost.

2.4.3. Feasibility Constraints

Candidate remediation combinations were screened against technological compatibility and project-level engineering constraints. The technological compatibility screening excluded configurations with conflicting treatment mechanisms, such as pairing in situ thermal desorption with in situ bioremediation within the same plot. At the project level, combinations were excluded when the total remediation cost exceeded CNY 94.5 million (approximately USD 13.90 million, based on the exchange rate at the time of manuscript revision: USD 1 = CNY 6.7990) or the total remediation duration exceeded 42 months, reflecting case-specific management requirements. The remaining combinations formed the feasible set for subsequent optimization.

2.5. Preference-Guided Selection of Remediation Alternatives

2.5.1. Pareto Search Using NSGA-II

NSGA-II was used to identify Pareto non-dominated remediation combinations under the simultaneous minimization of carbon emissions, remediation duration, and cost [37]. The optimization was implemented in Python 3.13.9 using DEAP 1.4.3. Each remediation combination was represented by a five-element integer vector, in which the five elements indicated the technologies selected for plots S1, S2, S3, W1, and W2, respectively. The algorithm was run with a population of 150 for 80 generations using uniform crossover, uniform integer mutation [38], and a fixed random seed of 42. Based on fast non-dominated sorting and crowding-distance preservation, NSGA-II generated the Pareto set that described the trade-off relationships among the three objectives and was used in the subsequent preference analysis. Other NSGA-II parameter settings are provided in Table S11, and the computational workflow is described in Text S4. The input data for NSGA-II are presented in Table S12.

2.5.2. Preference Filtering Using LO

Using the Pareto set generated by NSGA-II as input, LO was used to retain the best-ranked combinations for the preferred objective [39]. For a preferred objective r , the retained preference set was defined as Equation (4):

$$P_r = \{k \in P | \text{rank}_r(k) \leq \lceil \rho |P| \rceil\} \quad (4)$$

where P is the Pareto set, P_r is the retained set under preferred objective r , ρ is the screening ratio, and $\text{rank}_r(k)$ is the rank of combination k after sorting the Pareto combinations by objective r in ascending order. Here, r denotes the preferred objective, whereas m is used as the general index for the three objectives. Because all objectives were minimized, a lower

rank indicates better performance for the preferred objective. In the hybrid framework, $\rho = 0.15$ was used as the baseline screening ratio.

2.5.3. Final Recommendation Using Ideal-Point Distance

Within each retained preference set, the ideal-point distance method was used to select the final recommended remediation combination [40]. Because carbon emissions, remediation duration, and cost are all minimization objectives, each objective was normalized using a reverse min–max transformation, as shown in Equation (5):

$$z_{m,k} = (f_m^{\max} - F_{m,k}) / (f_m^{\max} - f_m^{\min}) \quad (5)$$

where $z_{m,k}$ is the normalized score of objective m for remediation combination k , $F_{m,k}$ is defined in Equation (3), and $f_m^{\max}$ and $f_m^{\min}$ are the maximum and minimum values of objective m in the Pareto set. Under this transformation, lower original objective values correspond to higher normalized scores, and the best observed value of each objective is mapped to 1.

The distance from each remediation combination in the retained preference set to the ideal point was then calculated as Equation (6):

$$D_k = \left[\sum_{m=1}^3 w_m (1 - z_{m,k})^2 \right]^{1/2}, k \in P_r \quad (6)$$

where D_k is the ideal-point distance for remediation combination $k \in P_r$, and w_m is the weight assigned to objective m . Equal weights were used for the three objectives, with $w_m = 1/3$, because management preference had already been introduced through LO-based filtering. The remediation combination with the smallest D_k in P_r was selected as the final recommendation. The normalization and ideal-point distance calculations were performed in Microsoft Excel 2019 using Equations (5) and (6).

2.6. Model Comparison, Sensitivity Analysis, and Stability Analysis

To evaluate the role of the NSGA-II-LO procedure, LO and NSGA-II were applied separately as benchmark procedures. In the LO benchmark, the feasible set was filtered sequentially according to the specified priority order, with 5% of the combinations retained at each step. In the NSGA-II benchmark, the Pareto set was used without LO-based preference filtering, and three boundary alternatives were selected to represent the lowest carbon emissions, shortest remediation duration, and lowest cost, respectively.

Three management preference scenarios were considered: carbon-first, duration-first, and cost-first. These scenarios prioritized carbon emissions, remediation duration, and cost, respectively. In the LO benchmark, the corresponding priority orders were carbon emissions $\rightarrow$ cost $\rightarrow$ remediation duration, remediation duration $\rightarrow$ cost $\rightarrow$ carbon emissions, and cost $\rightarrow$ carbon emissions $\rightarrow$ remediation duration. In the hybrid decision process, the same primary preference was used to define the retained preference set P_r , and the final recommended remediation combination was selected using the ideal-point distance method.

Sensitivity analysis of the screening ratio was conducted by changing the screening ratio ρ in Equation (4). The baseline value $\rho = 0.15$ was compared with a stricter setting $\rho = 0.05$ and a more relaxed setting $\rho = 0.50$. These settings helped examine how the retained preference range affected the objective values and technology configurations of the recommended remediation combinations.

Stability analysis was conducted by repeating NSGA-II with ten predetermined random seeds, including the baseline seed of 42, while keeping all other settings un-

changed [41]. Stability was assessed based on the number of Pareto non-dominated solutions, the overlap between Pareto sets, and the consistency of the recommended technology combinations and objective values under the three preference scenarios. For each run, the Jaccard overlap between its Pareto set P_s and the seed-42 Pareto set P_{42} was calculated using Equation (7):

$$J = |P_s \cap P_{42}| / |P_s \cup P_{42}| \quad (7)$$

where $|\cdot|$ denotes the number of solutions in a set. A J value closer to 1 indicates that a larger proportion of identical Pareto non-dominated technology combinations are present in both sets and therefore indicates greater consistency across random seeds. The recommended technology combinations and their corresponding objective values obtained from the ten runs were also compared to determine whether the random seed affected the final recommendations. In addition, Origin 2021 was used to prepare the figures.

3. Results

3.1. Candidate and Feasible Remediation Alternative

A total of 16,807 candidate remediation combinations were generated by systematically combining the plot-specific feasible technologies across the five contaminated plots (Table S7). The stepwise screening process from candidate to feasible remediation alternatives is summarized in Table 2. Technological compatibility screening first removed 1372 combinations with conflicting treatment mechanisms. After the objective values of the remaining combinations were quantified, 13,234 additional combinations were excluded because they exceeded the project-level engineering constraints on total remediation cost or duration. Finally, 2201 feasible remediation combinations were retained for subsequent multi-objective optimization.

Table 2. Screening of candidate remediation alternatives to identify feasible alternatives.

Phase	Action	Number Excluded	Number Remaining	Screening Basis
Initial generation	Combined 7 feasible technologies across 5 plots	0	16,807	$7^5 = 16,807$ candidate remediation combinations
Screening of technological compatibility	Excluded combinations with conflicting treatment mechanisms	1372	15,435	Conflict between thermal desorption and bioremediation technologies
Screening of engineering constraint	Excluded combinations exceeding the cost or duration limit	13,234	2201	Total remediation cost > CNY 94.5 million or duration > 42 months
Final feasible alternatives	Retained alternatives satisfying both screening requirements	—	2201	Retained for multi-objective optimization (13.1% of the initial combinations)

Only 13.1% of the initially generated combinations remained feasible after constraint screening. This reduction shows that multi-plot remediation decision-making involves a large combinatorial solution space, but only a small proportion of alternatives satisfy both technological compatibility and project-level engineering constraints. By systematically generating cross-plot alternatives before applying constraint screening, the framework reduces the risk of overlooking feasible remediation alternatives that may not be included in manually predefined scenarios.

3.2. Technology Configurations Under Different Management Preferences

The recommended technology configurations differed among the three decision models and management preference scenarios (Figure 2). In the LO benchmark, the selected technology configurations were sensitive to the preference order. For the heavily contaminated S3 plot, the recommended technology shifted from soil vapor extraction (SVE) under the carbon-first scenario to ex situ cement kiln co-processing (CKC) under the duration-first scenario and to in situ thermal desorption combined with in situ chemical oxidation (ISTD + ISCO) under the cost-first scenario (Figure 2A(a–c)).

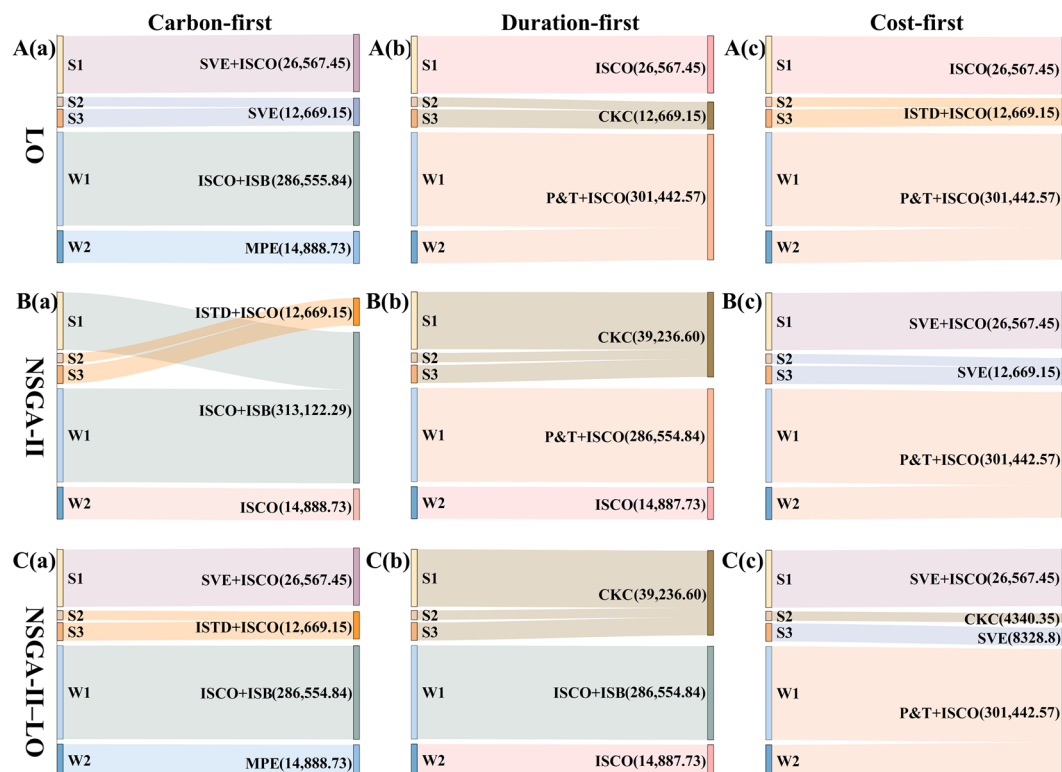


Figure 2. Technology configurations of recommended remediation combinations under different decision models and management preference scenarios: (A) LO, (B) NSGA-II, and (C) NSGA-II-LO; (a) carbon-first, (b) duration-first, and (c) cost-first scenarios. Numbers following technology names indicate the contaminated volume treated by the corresponding technology or combined technology (m^3).

The NSGA-II benchmark showed a different pattern because it selected objective-boundary combinations from the Pareto set without preference filtering. In the lowest-carbon-emission combination, four plots adopted in situ combined technologies, whereas the same four plots shifted to ex situ remediation technologies in the shortest-duration combination (Figure 2B(a–c)). This pattern indicates that NSGA-II effectively identifies objective extremes, but the resulting technology configurations can change substantially when different objective boundaries are selected.

Compared with the two benchmark models, NSGA-II-LO produced more selectively adjusted configurations across preferences (Figure 2C(a–c)). Under the carbon-first scenario, the recommended combination mainly relied on in situ ISCO-derived technologies. Under the duration-first scenario, CKC was selected for the soil plots to compress remediation duration. Under the cost-first scenario, CKC was assigned only to S2, which had the smallest contaminated soil volume, whereas extraction-derived technologies were used for larger-volume plots. Overall, the hybrid model showed smaller changes in cross-plot technology configurations than LO and did not rely on the objective-boundary combinations selected

by NSGA-II. Its recommended configurations reflected both plot-specific remediation requirements and the specified management preference.

3.3. Multi-Objective Performance of Recommended Remediation Alternatives

NSGA-II generated 89 Pareto non-dominated remediation combinations (Figure S2), and their technology configurations and objective values are provided in Table S13. The distribution of these combinations showed trade-offs among carbon emissions, remediation duration, and cost. Combinations with lower carbon emissions generally required longer remediation duration, whereas combinations with shorter remediation duration were usually associated with higher carbon emissions and cost.

To compare the recommended alternatives from different decision models, the three objective values were normalized using a reverse min–max transformation based on the extrema of the Pareto set, with lower original values corresponding to higher normalized scores (Figure 3). The radar profiles showed clear differences among the three decision models. In the LO benchmark, the recommended alternatives generally had broad and relatively even profiles across the three objectives, but their scores along the preferred-objective axes were limited in some scenarios (Figure 3a). In the NSGA-II benchmark, each boundary alternative reached the maximum normalized score for its corresponding objective, while the scores for the other objectives decreased markedly, resulting in more uneven profiles (Figure 3b). In comparison, the recommended alternatives from the hybrid NSGA-II–LO model showed clearer extension along the preferred-objective axes while maintaining moderate scores for the non-preferred objectives (Figure 3c).

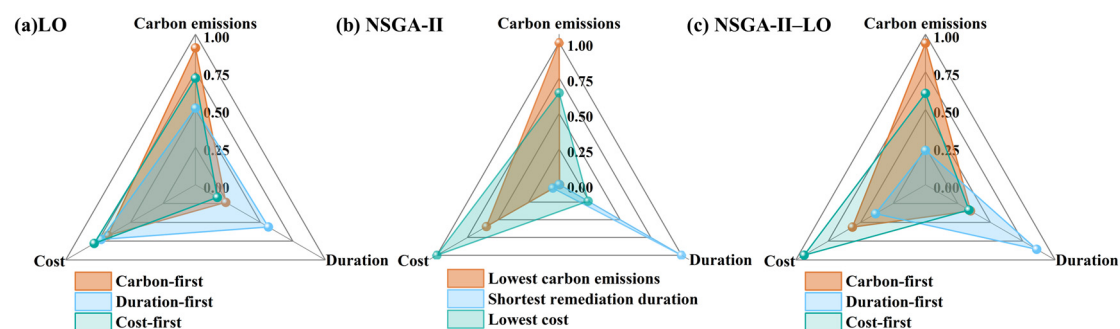


Figure 3. Comprehensive performance of recommended remediation alternatives under different management preference scenarios for (a) LO, (b) NSGA-II, and (c) NSGA-II–LO.

4. Discussion

4.1. Mechanisms Behind the Improved Performance of the Hybrid Model

The model comparison indicates that the timing and form of preference incorporation affected the final remediation alternatives. LO introduced the primary management priority before the feasible trade-off space was sufficiently explored, whereas NSGA-II identified boundary alternatives from the Pareto set without selecting according to a specific priority. In contrast, the NSGA-II–LO procedure first retained Pareto alternatives and then narrowed the solution set according to the preferred objective. Under the three preference scenarios, LO generally retained higher scores for the non-preferred objectives, but its preferred-objective score was lower than those of the NSGA-II and NSGA-II–LO recommendations (Figure 4, Table S14). For example, under the duration-preference scenario, the normalized duration score of the LO alternative was 0.56, whereas its cost score reached 0.73 (Figure 4b). NSGA-II showed the opposite pattern. Because its recommendations were selected from objective-boundary alternatives in the Pareto set, the preferred objective had the best score, whereas the other two objectives received much lower scores. In the same

duration-preference scenario, the NSGA-II alternative achieved the shortest remediation duration, but its normalized carbon-emission and cost scores were both below 0.05. The NSGA-II-LO procedure gave a less one-sided recommendation. It kept a relatively high score for the preferred objective and higher scores for the non-preferred objectives than the NSGA-II boundary alternative. This type of result is more practical for remediation management, where one objective may be prioritized but the remaining objectives still need to be considered.

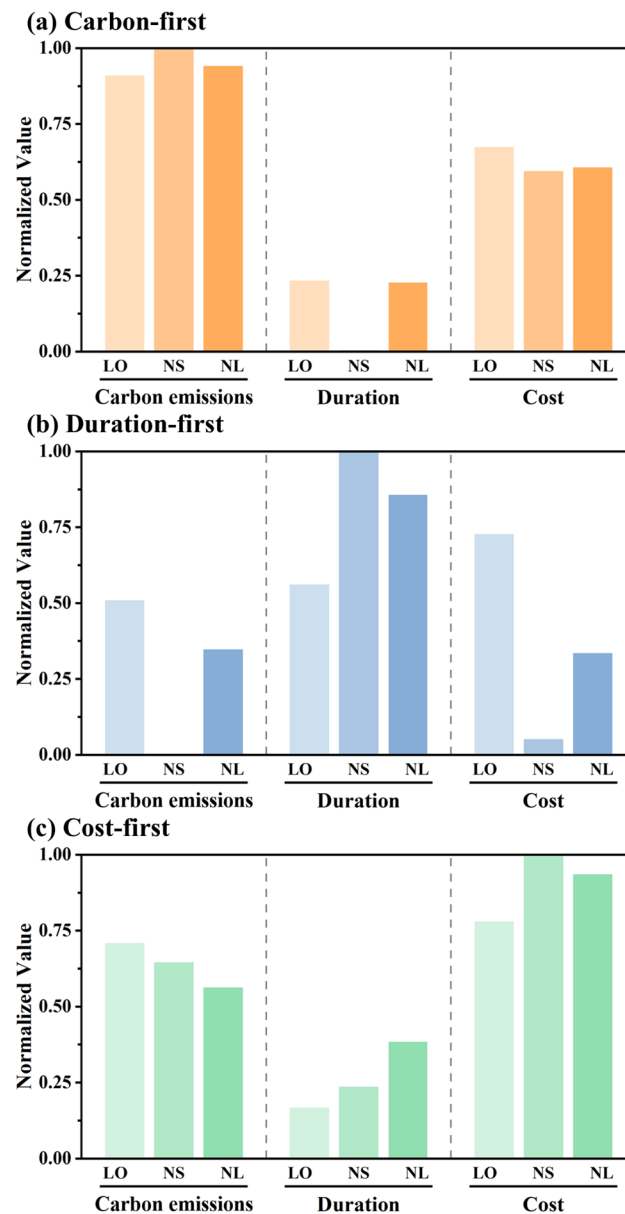


Figure 4. Multi-objective performance of recommended remediation alternatives obtained using three decision procedures under different management preference scenarios: (a) carbon-first, (b) duration-first, and (c) cost-first scenarios. LO represents the Linear Ordering benchmark, NS represents the NSGA-II benchmark, and NL represents the hybrid NSGA-II-LO procedure.

This pattern can first be explained by the technology configurations selected by the hybrid NSGA-II-LO model. The model made use of cross-plot synergies when similar technologies were suitable for adjacent plots. Under the duration-preference scenario, for example, the hybrid model selected CKC for S1, which was lightly contaminated, and for the other two soil-contaminated plots. This centralized configuration allowed fixed initial

inputs, such as site preparation and equipment mobilization, to be shared across a larger treatment volume. This is consistent with Liang et al. [42], who reported that fixed carbon emissions and remediation costs per unit mass can decrease by 25–27% as treatment scale increases. In comparison, LO selected ISCO only for S1, which limited the opportunity to use scale-related benefits across adjacent plots.

At the same time, it retained plot-specific matching when local contamination conditions required different treatment intensities. W1 provides another example. Although W1 was only lightly contaminated, its remediation volume reached 286,554.8 m³, accounting for 84.1% of the total remediation volume. For such a large groundwater treatment volume, assigning a high-intensity combined technology such as P&T + ISCO, as in the LO and NSGA-II benchmarks, may introduce unnecessary energy input [39]. The hybrid NSGA-II–LO recommendation selected ISCO + ISB for W1, reducing operating cost by 16.5% while still meeting remediation requirements. This is consistent with the source–plume zoning concept proposed by ITRC [43], in which technology intensity is matched to contaminant distribution and hydraulic conditions rather than applied uniformly across the whole site. Overall, the hybrid recommendation reflected both coordination among contaminated plots and plot-specific treatment needs.

At the model level, these differences were related to how each method selected the final recommendation. LO is easy to implement because it screens alternatives according to a predefined priority order, but its preference-screening mechanism is limited by local, stepwise truncation [33,35]. During the duration-preference scenario, for example, the second-level LO comparison retained only alternatives within a cost range of CNY 65.62–67.94 million. As a result, the hybrid NSGA-II–LO recommendation, with a total cost of CNY 81.24 million, was excluded at this stage even though it showed better overall trade-off performance (Table S15). This example shows that LO may miss some alternatives when an intermediate screening condition is applied too early.

NSGA-II follows a different logic from LO. It uses a global multi-objective search to generate Pareto alternatives, but the resulting Pareto set still contains many candidate alternatives that require further selection [32]. Without preference guidance, the most readily identifiable options are often objective-boundary alternatives. These alternatives are useful for showing the best attainable value of each single objective, but they may be less suitable as direct engineering recommendations when the other objectives receive low scores. Adding MCDA after Pareto search can help compare Pareto alternatives, but it also introduces additional criteria, weighting, and normalization assumptions, which may increase the complexity of the decision process [44].

The hybrid NSGA-II–LO model addresses this issue by applying preference filtering after the global Pareto search. It first uses NSGA-II to retain Pareto alternatives from the global multi-objective search, then applies LO to introduce management preference within the Pareto set, and finally uses ideal-point distance comparison to select the recommended alternative. This process preserves the comparison of Pareto alternatives across carbon emissions, remediation duration, and cost, while introducing management preference before the final recommendation. It also explains why the hybrid model could retain a relatively high score for the preferred objective while keeping the non-preferred objectives at more acceptable levels.

4.2. Preference Screening Ratio as a Management Tolerance Parameter

The preference screening ratio ρ represents the tolerance range used to retain Pareto alternatives under a specified management preference. In practical remediation projects, this tolerance may vary with budget constraints, land-delivery schedules, regulatory requirements, and risk acceptance. To examine the sensitivity of the hybrid NSGA-II–LO

model to this parameter, ρ was tested from 5% to 50%, with $\rho = 15\%$ used as the baseline. The results (Figure 5, Table 3 and Table S16) show that changes in ρ affected the recommended alternatives, but the main technology configurations remained relatively stable. In most scenarios, only one or two plot-level technologies changed, suggesting that the model output was not highly sensitive to moderate changes in the screening ratio (Table 3).

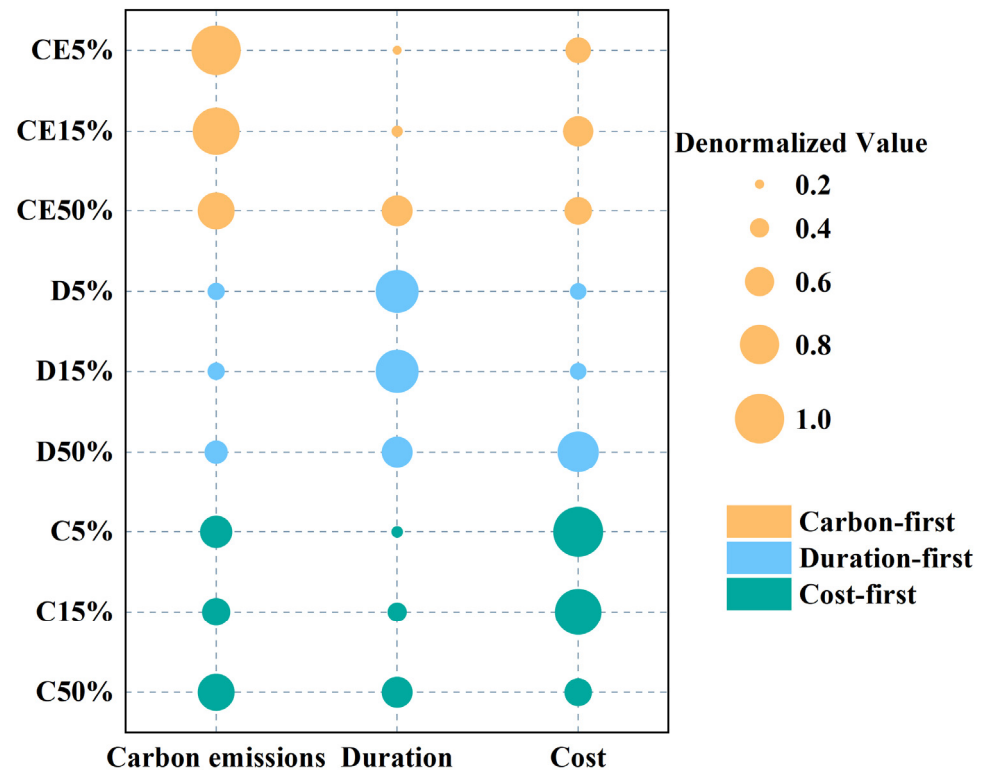


Figure 5. Multi-objective performance of recommended remediation alternatives from the hybrid NSGA-II-LO model under different preference screening ratios ρ . CE, D, and C denote carbon-first, duration-first, and cost-first scenarios, respectively; the following percentage indicates the value of ρ . For example, CE5% represents the carbon-first scenario with $\rho = 5\%$.

Table 3. Technology configurations and ideal-point distances of recommended remediation alternatives from the hybrid NSGA-II-LO model under different preference screening ratios ρ .

Preferences ¹	ρ ²	S1 *	S2 *	S3 *	W1 *	W2 *	ID ³
Carbon	5%	ISCO	ISTD + ISCO	ISTD + ISCO	ISCO + ISB	ISCO	0.55
	15%	SVE + ISCO	ISTD + ISCO	ISTD + ISCO	ISCO + ISB	MPE	0.50
	50%	SVE + ISCO	CKC	CKC	ISCO + ISB	MPE	0.37
Duration	5%	CKC	CKC	CKC	ISCO + ISB	ISCO	0.54
	15%	CKC	CKC	CKC	ISCO + ISB	ISCO	0.44
	50%	SVE + ISCO	CKC	CKC	ISCO + ISB	MPE	0.37
Cost	5%	SVE + ISCO	SVE	SVE	P&T + ISCO	P&T + ISCO	0.49
	15%	SVE + ISCO	CKC	SVE	P&T + ISCO	P&T + ISCO	0.54
	50%	SVE + ISCO	CKC	CKC	P&T + ISCO	P&T + ISCO	0.39

¹ Carbon, duration, and cost denote carbon-first, duration-first, and cost-first management preference scenarios, respectively. ² ρ = preference-screening ratio. ³ ID = ideal-point distance calculated using Euclidean distance. * SVE = soil vapor extraction; ISCO = in situ chemical oxidation; ISTD = in situ thermal desorption; ISB = in situ bioremediation; CKC = cement kiln co-processing; MPE = multi-phase extraction; P&T = pump and treat. "+" indicates combined application of two technologies in the same plot.

Although the main technology configurations changed only slightly, the objective values responded more clearly to changes in ρ . A stricter screening ratio retained alternatives

with stronger performance in the preferred objective, whereas a more relaxed ratio allowed greater improvement in the non-preferred objectives. Under the carbon-first scenario, when ρ was increased to 50%, carbon emissions increased by 176.7%, but remediation duration decreased by 28.6%, and the ideal-point distance decreased by 32.7% (Figure 5). The cost-first scenario showed a similar pattern. When $\rho = 50\%$, the carbon-first and cost-first scenarios led to the same recommended alternative, indicating that low-carbon and low-cost preferences may converge when the screening range is sufficiently broad (Table 3). This is consistent with previous studies showing that energy use, material input, and transport intensity can jointly affect carbon emissions and remediation costs [45,46].

The duration-first scenario showed a different response. When ρ was reduced to 5%, the recommended alternative was the same as that obtained at the 15% baseline, indicating limited sensitivity to a stricter screening ratio in this scenario. When ρ was relaxed to 50%, remediation duration increased by 28.0%, whereas cost and carbon emissions decreased by 23.2% and 15.2%, respectively. The ideal-point distance also decreased by 27.8%. This suggests that a wider screening range allowed the model to give up part of the duration advantage in exchange for lower cost and carbon emissions.

The aforementioned variations in solution performance essentially reflect the model's adaptive adjustments to local technology configurations (Table 3). Further observation of these minor technology substitutions reveals that when ρ was too strict, such as 5%, the model placed stronger emphasis on the preferred objective and left less room for adjustment in the other objectives. Under the carbon-first scenario, for example, low-energy technologies such as ISCO and SVE were assigned to W2 and S3, respectively, to reduce calculated carbon emissions. However, for plots with relatively high contamination levels or stricter remediation requirements, these options would require careful engineering verification before implementation. This suggests that the lowest-carbon configuration is not necessarily the most suitable remediation configuration.

Conversely, when ρ was too relaxed, such as 50%, the preference filtering became less selective. The recommended alternatives more frequently included high-efficiency but more energy-intensive technologies, such as CKC and MPE. These technologies helped improve some non-preferred objectives, but they also reduced the distinction among different management preference scenarios. Consequently, the final recommendation became less sensitive to the stated management preference.

For the present case, $\rho = 15\%$ provided a reasonable middle setting. Under the carbon-first scenario, the model replaced ISCO with the more efficient MPE in W2 and selected SVE + ISCO for S1. These local adjustments increased part of the short-term energy use or cost, but improved engineering suitability and the overall trade-off among carbon emissions, remediation duration, and cost. Therefore, the 15% screening ratio should be interpreted as a case-specific reference rather than a universal threshold.

The preference-guided recommendations were also stable across the tested NSGA-II random seeds. Across the ten runs, the number of Pareto non-dominated solutions ranged from 89 to 90 (89.60 ± 0.52), and the Jaccard overlap with the seed-42 Pareto set was 0.98–1.00 (Table S17). Although the number and composition of Pareto solutions varied slightly among the runs, all runs yielded identical recommended technology combinations and objective values under each of the three preference scenarios. Thus, the small seed-related differences in the Pareto sets did not affect the final recommendations.

Taken together, the sensitivity and stability analyses suggest that the hybrid NSGA-II-LO model produced relatively stable recommendations within the tested settings. The sensitivity analysis suggests that, within the tested range of ρ , the hybrid NSGA-II-LO model produced relatively stable recommendations, with changes mainly reflected in a small number of technology substitutions and in the degree of trade-off among objectives.

These findings support the applicability of the hybrid framework in the present case, while further applications are needed to examine its performance under larger and more diverse remediation combinations. In the present case, the added preference-screening and final-selection calculations were manageable because the Pareto set was limited. For industrial parks with more plots and more candidate technologies, computational burden and parameter sensitivity may become more important. Future studies should therefore benchmark the framework across larger portfolio spaces and multiple cases.

4.3. Implications for Low-Carbon and Adaptive Remediation Management

Beyond selecting a single recommended alternative, the model outputs can help explain how technology roles change under different management preferences. To derive management implications for multi-plot remediation in contaminated industrial parks, this study examined the application frequencies of technologies across different preference ranges and the concentration of energy-intensive technologies in heavily contaminated plots under schedule-compression requirements among the 89 Pareto alternatives (Figure 6). The results indicate that different technologies played different roles as the preference setting changed. Under the carbon-first scenario (Figure 6a), low-energy in situ technologies, such as in situ chemical oxidation combined with in situ bioremediation (ISCO + ISB), were more frequently selected to control carbon emissions and environmental disturbance. Under the duration-first scenario (Figure 6b), high-efficiency ex situ technologies, such as CKC, were more frequently introduced to shorten the remediation duration. Overall, ISCO-related technologies accounted for up to 62% of applications across all scenarios, suggesting that they can serve as baseline options for carbon and cost control. By contrast, CKC and other high-efficiency technologies can be used as supplementary options when schedule compression becomes a dominant requirement. This distinction helps clarify how low-energy in situ technologies and high-efficiency ex situ technologies can be combined under different management priorities.

In practice, remediation projects in industrial parks often face strict schedule constraints related to land transfer or redevelopment delivery [11]. Under strong duration constraints, heavily contaminated plots may become bottlenecks in the overall remediation process [47]. S3 provides a clear example. Although it accounted for only 2.4% of the total remediation volume, its maximum exceedance of the remediation target reached 98.2 times. As a result, its remediation progress had a strong influence on whether the overall project could meet the required schedule. The analysis suggests that compressing the remediation duration may increase the carbon burden of the heavily contaminated S3 plot, which is consistent with the trade-off between time reduction and environmental benefit discussed by Lemming et al. [15]. As shown in Figure 6d, when the required duration was shortened to below 31.9 months, more than 60% of the preferred Pareto alternatives selected CKC or soil thermal desorption for S3. This technology shift was associated with an increase of approximately 10,962 t CO₂ eq in carbon emissions, suggesting that tighter schedule requirements may lead to the concentrated use of energy-intensive technologies in heavily contaminated plots such as S3.

These preference-related technology configuration patterns and the concentration of energy-intensive technologies in heavily contaminated plots under schedule-compression requirements provide practical implications for both planning and implementation. During the planning stage, managers can adjust preference settings according to budget limits, schedule requirements, and low-carbon objectives, rather than comparing plot-level technologies separately. For example, within a medium cost range of CNY 70.35–79.97 million, introducing combined processes such as ISTD + ISCO may reduce dependence on a single ex situ thermal treatment route while maintaining an acceptable trade-off among carbon

emissions, remediation duration, and cost. During the implementation stage, the model outputs can help determine the critical duration threshold at which heavily contaminated plots such as S3 are likely to shift toward energy-intensive technologies. Once this threshold is recognized, managers can prioritize resource allocation, consider cleaner energy supply, optimize equipment operation, or adjust construction sequencing for these plots. In this sense, the framework is not only a tool for selecting a final alternative, but also a way to support adaptive adjustment during remediation planning and implementation.

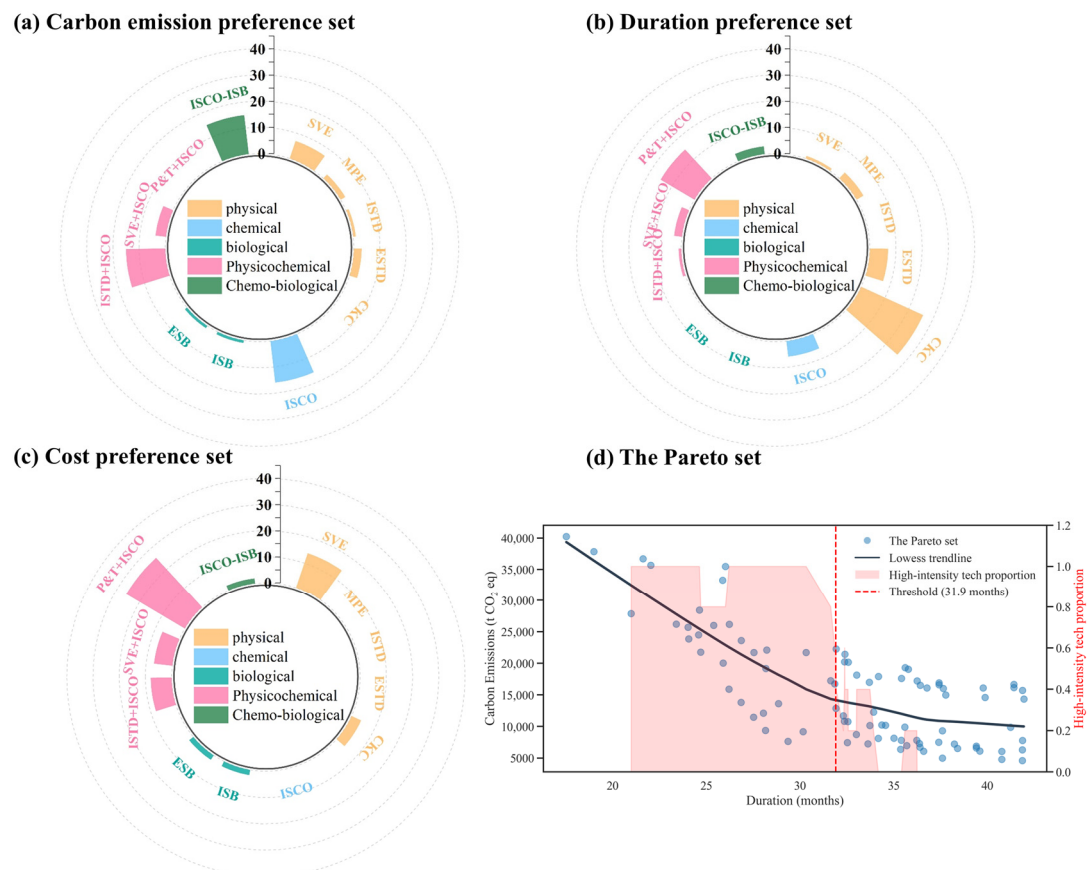


Figure 6. Technology application frequencies in recommended Pareto alternatives from the hybrid NSGA-II–LO model under different management-preference sets: (a) carbon-first, (b) duration-first, and (c) cost-first scenarios; and (d) application frequencies of energy-intensive ex situ technologies, including CKC and ESTD, for the heavily contaminated S3 plot under different duration requirements.

4.4. Limitations and Future Refinement

This study has four limitations. First, the sustainability-oriented assessment focused on carbon emissions, remediation duration, and cost, while environmental impacts were considered during plot-level technology screening. Social acceptance, long-term ecological recovery, and benefits from land reuse were not included because consistent data were unavailable [11,14]. Second, cost was estimated at the planning stage and treated as static. It therefore does not reflect the time value of money or changes in energy prices and financing conditions. Nor does it include the timing of land-reuse benefits or the effects of carbon pricing and subsidies. Future studies could use discounted life-cycle cost or net present value to account for dynamic economic factors [16,48]. Third, the technology parameters and cross-plot synergy deductions were derived from published studies, engineering cases, and case-specific evidence. These parameters should be updated with full-scale project and monitoring data when they become available. Fourth, the framework was tested in one contaminated industrial park. Further applications are needed to evaluate its performance

in multiple countries and under different regulatory contexts and economic scenarios. Tests at sites with different contamination and hydrogeological conditions are also needed to determine whether the preference-screening ratio and decision process remain reliable [19]. The sensitivity and stability analyses examined the preference-screening ratio and random-seed effects, but did not test how uncertainty in technology performance and synergy estimates would affect the recommendations. Monitoring data could then be used to revise these inputs during project implementation.

5. Conclusions

This study developed a preference-guided decision framework for translating plot-level technology screening into multi-plot remediation alternative selection in contaminated industrial parks. The framework was applied to a contaminated industrial park in northern China. The case study showed that the recommended alternatives prioritized the specified sustainability indicator (carbon emissions, remediation duration, or cost) while keeping the other objectives within a reasonable range. The sensitivity analysis showed that the preference screening ratio affected the balance between preference strength and overall trade-off, with 15% providing a suitable setting for the present case. Beyond selecting final remediation alternatives, the Pareto alternatives and preference-screening results provide a basis for feasible technology adjustments when schedule, budget, or low-carbon requirements change. Overall, the framework provides a practical approach for moving from plot-level technology screening to preference-informed multi-plot remediation decision-making. Future work can refine the framework by incorporating broader sustainability indicators and dynamic economic and financial analysis, using monitoring data, and applying the framework to additional contaminated industrial parks.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su18157647/s1>, Text S1: Method for plot-level technology screening and evaluation; Text S2: Quantification method for feasible technology parameters; Text S3: Quantification method for synergistic benefit parameters; Text S4: Computational workflow of hybrid NSGA-II-LO model and NSGA-II benchmark; Table S1: Initial screening table for soil remediation technologies; Table S2: Initial screening table for groundwater remediation technologies; Table S3: Indicators and weights of the comprehensive index method; Table S4: Scoring criteria for technology suitability indicators; Table S5: General ratings of soil remediation technologies across suitability indicators; Table S6: General ratings of groundwater remediation technologies across suitability indicators; Table S7: Technology screening and selection results for each plot; Table S8: Feasible technology parameters for S1, S2, and S3; Table S9: Feasible technology parameters for W1 and W2; Table S10: Synergistic benefit types and parameters; Table S11: NSGA-II implementation and parameter settings; Table S12: Input data of NSGA-II; Table S13: Output data of NSGA-II; Table S14: Performance comparison of recommended remediation combinations among three decision procedures under different management preferences; Table S15: LO benchmark screening process; Table S16: Performance comparison of recommended remediation combinations from the NSGA-II-LO procedure under different preference-screening ratios q ; Table S17: Stability of the NSGA-II and preference-guided recommendations across different random seeds; Figure S1: Suitability analysis of the top seven remediation technologies in the industrial park; Figure S2: Pareto front distribution [42,46,49–85].

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Abbreviations

The following abbreviations are used in this manuscript:

<i>cis</i> -1,2-DCE	<i>cis</i> -1,2-dichloroethylene
CKC	cement kiln co-processing
CNY	Chinese yuan
CO ₂ eq	carbon dioxide equivalent
CVOCs	chlorinated volatile organic compounds
DEAP	Distributed Evolutionary Algorithms in Python
EB	ethylbenzene
ESTD	ex situ thermal desorption
FRTR	Federal Remediation Technologies Roundtable
GIS	geographic information system
ISB	in situ bioremediation
ISCO	in situ chemical oxidation
ISTD	in situ thermal desorption
ITRC	Interstate Technology & Regulatory Council
LCA	life cycle assessment
LCSA	life cycle sustainability assessment
LO	lexicographic optimization
MCDA	multi-criteria decision analysis
MEE	Ministry of Ecology and Environment of the People's Republic of China
MOO	multi-objective optimization
MPE	multi-phase extraction
NSGA-II	non-dominated sorting genetic algorithm II
P&T	pump and treat
PCE	perchloroethylene
SVE	soil vapor extraction
TCE	trichloroethylene
TPH	total petroleum hydrocarbons
VC	vinyl chloride
VOCs	volatile organic compounds

References

1. Yong, G.; Zhao, H. Industrial Park Management in the Chinese Environment. *J. Clean. Prod.* **2009**, *17*, 1289–1294. [[CrossRef](#)]
2. Wang, N.; Guo, J.; Zhang, X.; Zhang, J.; Li, Z.; Meng, F.; Zhang, B.; Ren, X. The Circular Economy Transformation in Industrial Parks: Theoretical Reframing of the Resource and Environment Matrix. *Resour. Conserv. Recycl.* **2021**, *167*, 105251. [[CrossRef](#)]
3. Ren, F.; Wang, P.; Mei, D.; Li, Z.; Guo, Z.; Huang, L. Which Pollutants Should Be Prioritized for Control in Multipollutant Complex Contaminated Groundwater of Chemical Industrial Parks? *Environ. Sci. Technol.* **2025**, *59*, 6272–6284. [[CrossRef](#)] [[PubMed](#)]

4. Wang, S.; Zhang, J.; Sun, J.; Zhou, F.; Wang, P.; Qin, Z.; Zhao, Y.; Wang, S.; Han, Z.; Jiao, W. Spatial Distribution and Quantitative Source Identification of Heavy Metals in Soil of a Typical Industrial Park, East of China. *Bull. Environ. Contam. Toxicol.* **2025**, *114*, 48. [CrossRef] [PubMed]
5. Chen, D.; Feng, Q.; Gong, M. Contamination Characteristics and Source Identification of Groundwater in Xishan Coal Mining Area of Taiyuan Based on Hydrochemistry and Sulfur–Oxygen Isotopes. *Water* **2023**, *15*, 1169. [CrossRef]
6. Xiang, Z.; Wu, S.; Zhu, L.; Yang, K.; Lin, D. Pollution Characteristics and Source Apportionment of Heavy Metal(Loid)s in Soil and Groundwater of a Retired Industrial Park. *J. Environ. Sci.* **2024**, *143*, 23–34. [CrossRef] [PubMed]
7. Xu, M.; He, R.; Cui, G.; Wei, J.; Li, X.; Xie, Y.; Shi, P. Quantitative Tracing the Sources and Human Risk Assessment of Complex Soil Pollution in an Industrial Park. *Environ. Res.* **2024**, *257*, 119185. [CrossRef] [PubMed]
8. Critto, A.; Agostini, P. Using Multiple Indices to Evaluate Scenarios for the Remediation of Contaminated Land: The Porto Marghera (Venice, Italy) Contaminated Site. *Environ. Sci. Pollut. Res.* **2009**, *16*, 649–662. [CrossRef] [PubMed]
9. Xiao, M.; Li, X.; Zhang, H.; Meng, H.; Dong, J. Environmental Impact Assessment and Remediation Decision-Making of a Contaminated Megasite: Combining LCA and IO-LCA. *J. Clean. Prod.* **2024**, *462*, 142586. [CrossRef]
10. Chen, D.; Wang, X.; Luo, X.; Huang, G.; Tian, Z.; Li, W.; Liu, F. Delineating and Identifying Risk Zones of Soil Heavy Metal Pollution in an Industrialized Region Using Machine Learning. *Environ. Pollut.* **2023**, *318*, 120932. [CrossRef] [PubMed]
11. Hou, D.; Al-Tabbaa, A.; O'Connor, D.; Hu, Q.; Zhu, Y.-G.; Wang, L.; Kirkwood, N.; Ok, Y.S.; Tsang, D.C.W.; Bolan, N.S.; et al. Sustainable Remediation and Redevelopment of Brownfield Sites. *Nat. Rev. Earth Environ.* **2023**, *4*, 271–286. [CrossRef]
12. Li, X.; Wang, S.; Zhong, M.; Jiang, L.; Zhang, W.; Li, J. Carbon Reduction and Co-Benefits through Nature-Based Solution at a Large Petrochemical Contaminated Site in Beijing: Policy Implications for China. *J. Clean. Prod.* **2025**, *497*, 145172. [CrossRef]
13. Hu, G.; Liu, H.; Chen, C.; He, P.; Li, J.; Hou, H. Selection of Green Remediation Alternatives for Chemical Industrial Sites: An Integrated Life Cycle Assessment and Fuzzy Synthetic Evaluation Approach. *Sci. Total Environ.* **2022**, *845*, 157211. [CrossRef] [PubMed]
14. Rosén, L.; Back, P.-E.; Söderqvist, T.; Norrman, J.; Brinkhoff, P.; Norberg, T.; Volchko, Y.; Norin, M.; Bergknut, M.; Döberl, G. SCORE: A Novel Multi-Criteria Decision Analysis Approach to Assessing the Sustainability of Contaminated Land Remediation. *Sci. Total Environ.* **2015**, *511*, 621–638. [CrossRef] [PubMed]
15. Lemming, G.; Hauschild, M.Z.; Chambon, J.; Binning, P.J.; Bulle, C.; Margni, M.; Bjerg, P.L. Environmental Impacts of Remediation of a Trichloroethene-Contaminated Site: Life Cycle Assessment of Remediation Alternatives. *Environ. Sci. Technol.* **2010**, *44*, 9163–9169. [CrossRef] [PubMed]
16. Huysegoms, L.; Rousseau, S.; Cappuyns, V. Chemical or Natural? Including LCA in Social CBA to Compare Remediation Alternatives for a Dry-Cleaning Facility. *Sustainability* **2019**, *11*, 1975. [CrossRef]
17. Carlon, C.; Critto, A.; Ramieri, E.; Marcomini, A. DESYRE: Decision Support System for the Rehabilitation of Contaminated Megasites. *Integr. Environ. Assess. Manag.* **2007**, *3*, 211–222. [CrossRef] [PubMed]
18. Federal Remediation Technologies Roundtable (FRTR). Technology Screening Matrix. 2020. Available online: <https://frtr.gov/matrix/> (accessed on 20 May 2024).
19. Braun, A.B.; Visentin, C.; Thomé, A. Design of a Central Tool for Sustainability Evaluation and Weighting to Decision-Making Support of Contaminated Soils Remediation. *J. Environ. Manag.* **2024**, *351*, 119624. [CrossRef] [PubMed]
20. Huysegoms, L.; Cappuyns, V. Critical Review of Decision Support Tools for Sustainability Assessment of Site Remediation Options. *J. Environ. Manag.* **2017**, *196*, 278–296. [CrossRef] [PubMed]
21. Schädler, S.; Morio, M.; Bartke, S.; Finkel, M. Integrated Planning and Spatial Evaluation of Megasite Remediation and Reuse Options. *J. Contam. Hydrol.* **2012**, *127*, 88–100. [CrossRef] [PubMed]
22. Song, Y.; Pan, S.; Jin, Y.; O'Connor, D.; Nathanail, P.; Bardos, P.; Kang, Y.; Zuo, X.; Zhang, H.; Hou, D. Comparative Life-Cycle Sustainability Assessment of Centralized and Decentralized Remediation Strategies at the City Level. *Sci. Total Environ.* **2024**, *919*, 170908. [CrossRef] [PubMed]
23. Nie, J.; Wang, Q.; Han, L.; Li, J. Synergistic Remediation Strategies for Soil Contaminated with Compound Heavy Metals and Organic Pollutants. *J. Environ. Chem. Eng.* **2024**, *12*, 113145. [CrossRef]
24. Xiang, L.; Harindintwali, J.D.; Wang, F.; Redmile-Gordon, M.; Chang, S.X.; Fu, Y.; He, C.; Muhoza, B.; Brahushi, F.; Bolan, N.; et al. Integrating Biochar, Bacteria, and Plants for Sustainable Remediation of Soils Contaminated with Organic Pollutants. *Environ. Sci. Technol.* **2022**, *56*, 16546–16566. [CrossRef] [PubMed]
25. Saito, H.; Goovaerts, P. Selective Remediation of Contaminated Sites Using a Two-Level Multiphase Strategy and Geostatistics. *Environ. Sci. Technol.* **2003**, *37*, 1912–1918. [CrossRef] [PubMed]
26. Zhao, Y.; Lv, Y.; Lu, Z.; Wu, P.; Li, B.; Zeng, J. Hierarchical Zoning and Intelligent Remediation Strategy Selection for Heavy Metal Contaminated Smelting Sites. *J. Environ. Sci.* **2026**; in press. [CrossRef]
27. DeCarolis, J.F.; Babae, S.; Li, B.; Kanungo, S. Modelling to Generate Alternatives with an Energy System Optimization Model. *Environ. Model. Softw.* **2016**, *79*, 300–310. [CrossRef]

28. Jin, Y.; Hou, D.; Tian, L.; Wang, L.; Song, Y. Multi-Objective Optimization for Brownfield Remediation on the Basis of Land Use Planning. *China Environ. Sci.* **2021**, *41*, 787–800. [\[CrossRef\]](#)
29. Fienen, M.N.; Corson-Dosch, N.T.; Jahn, K.L.; White, J.T. Comparing Single and Multiple Objective Constrained Optimization Algorithms for Tuning a Groundwater Remediation System. *Environ. Model. Softw.* **2024**, *173*, 105952. [\[CrossRef\]](#)
30. Deb, K.; Pratap, A.; Agarwal, S.; Meyarivan, T. A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II. *IEEE Trans. Evol. Comput.* **2002**, *6*, 182–197. [\[CrossRef\]](#)
31. Deb, K.; Sundar, J. Reference Point Based Multi-Objective Optimization Using Evolutionary Algorithms. In Proceedings of the 8th Annual Conference on Genetic and Evolutionary Computation, Seattle, WA, USA, 8–12 July 2006; pp. 635–642. [\[CrossRef\]](#)
32. Zhao, D.; Chen, Y.; Yuan, H.; Chen, D. Life Cycle Optimization Oriented to Sustainable Waste Management and Circular Economy: A Review. *Waste Manag.* **2025**, *191*, 89–106. [\[CrossRef\]](#) [\[PubMed\]](#)
33. Tascione, V.; Mosca, R.; Raggi, A. Optimizing the Environmental Performance of Integrated Waste Management Scenarios by Means of Linear Programming: A Case Study. *J. Clean. Prod.* **2016**, *112*, 3086–3096. [\[CrossRef\]](#)
34. Cisneros, J.M.; Grau, J.B.; Antón, J.M.; de Prada, J.D.; Cantero, A.; Degioanni, A.J. Assessing Multi-Criteria Approaches with Environmental, Economic and Social Attributes, Weights and Procedures: A Case Study in the Pampas, Argentina. *Agric. Water Manag.* **2011**, *98*, 1545–1556. [\[CrossRef\]](#)
35. Patel, S.P.; Gujarathi, A.M.; Khamisi, S.A. Optimization of Industrial Carbon Capture Process Using Gradient, Weight-Based, and Lexicographic Approach. *Clean. Chem. Eng.* **2025**, *11*, 100181. [\[CrossRef\]](#)
36. GB 36600-2018; Soil Environmental Quality Risk Control Standard for Soil Contamination of Development Land. Ministry of Ecology and Environment of the People's Republic of China (MEE): Beijing, China, 2018.
37. Dehghanian, F.; Mansour, S. Designing Sustainable Recovery Network of End-of-Life Products Using Genetic Algorithm. *Resour. Conserv. Recycl.* **2009**, *53*, 559–570. [\[CrossRef\]](#)
38. Chen, C.; Wen, Z.; Wang, Y.; Zhang, W.; Zhang, T. Multi-Objective Optimization of Technology Solutions in Municipal Solid Waste Treatment System Coupled with Pollutants Cross-Media Metabolism Issues. *Sci. Total Environ.* **2022**, *807*, 150664. [\[CrossRef\]](#) [\[PubMed\]](#)
39. Andersson, J. *A Survey of Multi-Objective Optimization in Engineering Design*; Department of Mechanical Engineering, Linköping University: Linköping, Sweden, 2000.
40. Cui, X.; Zhou, T.; Li, J.; Ji, M.; Li, L.; Jiang, B.; Li, S.; Liu, J. An Adaptive Stratification Algorithm for Sound Velocity Profile Based on NSGA-II Multi-Objective Optimization. *Ocean Eng.* **2026**, *344*, 123665. [\[CrossRef\]](#)
41. Črepinšek, M.; Liu, S.-H.; Mernik, M. Replication and Comparison of Computational Experiments in Applied Evolutionary Computing: Common Pitfalls and Guidelines to Avoid Them. *Appl. Soft Comput.* **2014**, *19*, 161–170. [\[CrossRef\]](#)
42. Liang, T.; Huo, M.; Yu, L.; Wang, P.; Zheng, J.; Zhang, C.; Wang, D.; Ding, A.; Li, F. Life Cycle Assessment-Based Decision-Making for Thermal Remediation of Contaminated Soil in a Regional Perspective. *J. Clean. Prod.* **2023**, *392*, 136260. [\[CrossRef\]](#)
43. Interstate Technology & Regulatory Council (ITRC). *Integrated DNAPL Site Strategy (IDSS-1)*; ITRC DNAPL Site Characterization and Remediation Team: Washington, DC, USA, 2011. Available online: <https://itrcweb.org/dnapl-site-strategy-guide/> (accessed on 13 November 2023).
44. Huang, J.; Tan, X.; Xie, Y.; Wu, X.; Dahn, S.L.; Duan, Z.; Ali, I.; Cao, J.; Ruan, Y. A New Approach to Explore and Assess the Sustainable Remediation of Chromium-Contaminated Wastewater by Biochar Based on 3E Model. *Chemosphere* **2024**, *353*, 141600. [\[CrossRef\]](#) [\[PubMed\]](#)
45. Amponsah, N.Y.; Wang, J.; Zhao, L. A Review of Life Cycle Greenhouse Gas (GHG) Emissions of Commonly Used Ex-Situ Soil Treatment Technologies. *J. Clean. Prod.* **2018**, *186*, 514–525. [\[CrossRef\]](#)
46. Meng, H.; Nie, Y.; Zhang, C.; Zhang, H.; Dong, J.; Deng, J.; Li, X. A Global Synthesis on Intensity of Greenhouse Gases Emissions from the Remediation of Contaminated Sites Based on LCA Methodology. *J. Clean. Prod.* **2025**, *498*, 145191. [\[CrossRef\]](#)
47. Stroo, H.F.; Leeson, A.; Marqusee, J.A.; Johnson, P.C.; Ward, C.H.; Kavanaugh, M.C.; Sale, T.C.; Newell, C.J.; Pennell, K.D.; Lebrón, C.A.; et al. Chlorinated Ethene Source Remediation: Lessons Learned. *Environ. Sci. Technol.* **2012**, *46*, 6438–6447. [\[CrossRef\]](#) [\[PubMed\]](#)
48. Söderqvist, T.; Brinkhoff, P.; Norberg, T.; Rosén, L.; Back, P.-E.; Norrman, J. Cost-Benefit Analysis as a Part of Sustainability Assessment of Remediation Alternatives for Contaminated Land. *J. Environ. Manag.* **2015**, *157*, 267–278. [\[CrossRef\]](#) [\[PubMed\]](#)
49. Wang, Z.; Chen, Z.; Ma, C.; Wennersten, R.; Sun, Q. Nationwide Evaluation of Urban Energy System Resilience in China Using a Comprehensive Index Method. *Sustainability* **2022**, *14*, 2077. [\[CrossRef\]](#)
50. Saaty, T.L. *The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation*; McGraw-Hill International Book Co.: New York, NY, USA, 1980.
51. Crawford, G.; Williams, C. A Note on the Analysis of Subjective Judgment Matrices. *J. Math. Psychol.* **1985**, *29*, 387–405. [\[CrossRef\]](#)
52. Li, X.; Yi, S.; Chen, W.; Cundy, A.B. Application of a Novel Multi-Criteria Decision Analysis Approach for Evaluating the Sustainability of Contaminated Site Management: An Example from China. *Environ. Impact Assess. Rev.* **2024**, *104*, 107327. [\[CrossRef\]](#)

53. Liu, T.; Yang, L.; Shi, Y.; Chen, X. Comprehensive Analysis of Site Soil Remediation Technology in China. *Chin. J. Ecol.* **2025**, *44*, 3815. [[CrossRef](#)]
54. Mittal, A.; Shukla, S. Remediation Technologies—A Comparative Study. *Mater. Sci. Forum* **2019**, *969*, 697–702. [[CrossRef](#)]
55. Yang, Z.; Wei, C.; Song, X.; Liu, X.; Tang, Z.; Liu, P.; Wei, Y. Thermal Conductive Heating Coupled with in Situ Chemical Oxidation for Soil and Groundwater Remediation: A Quantitative Assessment for Sustainability. *J. Clean. Prod.* **2023**, *423*, 138732. [[CrossRef](#)]
56. Cho, H.J.; Fiocco, R.J., Jr.; Daly, M.H. Soil Vapor Extraction and Chemical Oxidation to Remediate Chlorinated Solvents in Fractured Crystalline Bedrock: Pilot Study Results and Lessons Learned. *Remediat. J.* **2002**, *12*, 35–50. [[CrossRef](#)]
57. Chen, B.; Xu, J.; Zhu, L. Controllable Chemical Redox Reactions to Couple Microbial Degradation for Organic Contaminated Sites Remediation: A Review. *J. Environ. Sci.* **2024**, *139*, 428–445. [[CrossRef](#)] [[PubMed](#)]
58. Wu, F.; Zhu, K.; Ma, S.; Hu, W.; Wang, L.; Li, Y. Groundwater Pollution Remediation Technology and Its Application in Domestic Engineering. *Bull. Sci. Technol.* **2026**, *40*, 1–8. [[CrossRef](#)]
59. Li, W.; Zhang, M.; Wang, M.; Han, Z.; Liu, J.; Chen, Z.; Liu, B.; Yan, Y.; Liu, Z. Screening of Groundwater Remedial Alternatives for Brownfield Sites: A Comprehensive Method Integrated MCDA with Numerical Simulation. *Environ. Sci. Pollut. Res.* **2018**, *25*, 15844–15861. [[CrossRef](#)] [[PubMed](#)]
60. Xie, T.; Dang, Z.; Zhang, J.; Zhang, Q.; Zhang, R.-H.; Liao, C.-J.; Lu, G.-N. Decontamination of Dense Nonaqueous-Phase Liquids in Groundwater Using Pump-and-Treat and in Situ Chemical Oxidation Processes: A Field Test. *RSC Adv.* **2021**, *11*, 4237–4246. [[CrossRef](#)] [[PubMed](#)]
61. Honetschlagerová, L.; Martinec, M.; Škarohlíd, R. Coupling in Situ Chemical Oxidation with Bioremediation of Chloroethenes: A Review. *Rev. Environ. Sci. Biotechnol.* **2019**, *18*, 699–714. [[CrossRef](#)]
62. Dangi, M.B.; Urynowicz, M.A.; Schultz, C.L.; Budhathoki, S.; Dangi, S.R. Analysis of the Effects of in Situ Chemical Oxidation on Microbial Activity Using *Pseudomonas Putida* F1. *Heliyon* **2021**, *7*, e08665. [[CrossRef](#)] [[PubMed](#)]
63. Yang, Z.; Wei, C.; Sima, J.; Yan, S.; Yin, L.; Xian, A.; Wan, J.; Yang, J.; Song, X. Quantitative Sustainability Assessment for in Situ Electrical Resistance Heating Coupled with Steam Enhanced Extraction: An Effective Approach for the Development of Green Remediation Technologies. *Water Res.* **2024**, *267*, 122450. [[CrossRef](#)] [[PubMed](#)]
64. Chen, Z.; Chen, Z.; Li, Y.; Zhang, R.; Liu, Y.; Hui, A.; Cao, W.; Liu, J.; Bai, H.; Song, J. A Review on Remediation of Chlorinated Organic Contaminants in Soils by Thermal Desorption. *J. Ind. Eng. Chem.* **2024**, *133*, 112–121. [[CrossRef](#)]
65. Xue, C.; Fang, Z. Path of Carbon Emission Peaking and Carbon Neutrality in Soil Remediation Industry. *Environ. Eng.* **2022**, *40*, 231–238. [[CrossRef](#)]
66. Li, J.; Zhang, J.; Guo, J.; Wang, N. Soil Remediation Technology for Organic Polluted Land. *Green Build.* **2021**, *13*, 81–84.
67. Song, Z.; Yuan, S.; Chao, J.; Yang, W.; Wang, X.; Zheng, F. Application of Cement Kiln Thermal-Treatment Technology for Remediation of Cyanide-Contaminated Soil. *Environ. Sanit. Eng.* **2020**, *28*, 76–79. [[CrossRef](#)]
68. Meng, H.; Dong, J.; Zhang, H.; Xiao, M.; Li, X. Calculation Method and Case Analysis of Carbon Emissions for Risk Control and Management of Contaminated Sites. *China Environ. Sci.* **2023**, *43*, 368–375. [[CrossRef](#)]
69. Zheng, F.; Zhang, C.; Yuan, S.; Chao, J.; Song, Z. Engineering Practice of in Situ Chemical Oxidation of Pahs Contaminated Soil from Decommissioned Steelworks. *Environ. Sanit. Eng.* **2022**, *30*, 69–73. [[CrossRef](#)]
70. Zhang, J.; Zhu, Y.; Zhao, Z. Research on the Application of in-site Chemical Oxidation Technology in the Ground Water Remediation Engineering of Existing Waste Landfills. *Urban Manag. Sci. Technol.* **2024**, *25*, 69–72. [[CrossRef](#)]
71. Tian, P.; Zheng, J.; Du, Y.; Zhu, Y.; Zou, C.; Yang, S.; Zhou, H. Research on the Application of Soil Green Remediation Technology Evaluation for Petroleum Hydrocarbon Contaminated Sites Based on SEFA Method. *Environ. Pollut. Control* **2025**, *46*, 1149–1155. [[CrossRef](#)]
72. Xu, P.; Han, J.; Wang, D.; Xi, L.; Qu, C. Optimization and Application of Heterotopic Chemical Oxidation and Thermal Desorption Remediation Techniques for Soil Polluted by Organic Matter. *Environ. Sci. Technol.* **2023**, *36*, 30–34. [[CrossRef](#)]
73. Favara, P.; Gamlin, J. Utilization of Waste Materials, Non-Refined Materials, and Renewable Energy in in Situ Remediation and Their Sustainability Benefits. *J. Environ. Manag.* **2017**, *204*, 730–737. [[CrossRef](#)]
74. Orellana, R.; Cumsille, A.; Rojas, C.; Cabrera, P.; Seeger, M.; Cárdenas, F.; Stuardo, C.; González, M. Assessing Technical and Economic Feasibility of Complete Bioremediation for Soils Chronically Polluted with Petroleum Hydrocarbons. *J. Bioremediat. Biodegrad.* **2017**, *8*, 396. [[CrossRef](#)]
75. Busset, G.; Sangely, M.; Montrejaud-Vignoles, M.; Thannberger, L.; Sablayrolles, C. Life Cycle Assessment of Polychlorinated Biphenyl Contaminated Soil Remediation Processes. *Int. J. Life Cycle Assess.* **2012**, *17*, 325–336. [[CrossRef](#)]
76. Zhan, M.; Zhang, L.; Li, J.; Zhang, D.; Guo, Y.; Wang, Y. Field Experimental Study on the Application of Straw and Mushroom Residue in Biopile Remediation of Organically Contaminated Soil. *Jiangsu Agric. Sci.* **2015**, *43*, 300–304. [[CrossRef](#)]
77. GB/T 39791.1-2020; Technical Guidelines for Identification and Assessment of Environmental Damage—Environmental Elements—Part 1: Soil and Groundwater. Ministry of Ecology and Environment of the People’s Republic of China (MEE): Beijing, China, 2020.
78. Jin, J.; Yang, Y.; Wang, Z.; Zhang, W.; Zhou, Y.; Zhang, F.; Li, L.; Cui, C. Optimization of Low-Carbon Multi-Phase Extraction Remediation Well Locations in Contaminated Sites by Simulation. *Res. Environ. Sci.* **2023**, *36*, 1596–1606. [[CrossRef](#)]

79. Liu, P.; Sang, C.; Zhang, H.; Xiao, M.; Meng, H.; Li, X. Environmental Footprint Assessment of in Situ Chemical Oxidation Remediation for Contaminated Aquifer Based on SiteWise™ Method. *Acta Pedol. Sin.* **2024**, *62*, 448–458. [[CrossRef](#)]
80. Ministry of Ecology and Environment of the People's Republic of China (MEE). Chapter 7: Cases of Groundwater Pollution Remediation. In *Technical Manual for Risk Management and Remediation of Groundwater Pollution*; China Environment Publishing Group: Beijing, China, 2021; pp. 291–297.
81. Ni, Z.; Wang, Y.; Wang, Y.; Chen, S.; Xie, M.; Grotenhuis, T.; Qiu, R. Comparative Life-Cycle Assessment of Aquifer Thermal Energy Storage Integrated with in Situ Bioremediation of Chlorinated Volatile Organic Compounds. *Environ. Sci. Technol.* **2020**, *54*, 3039–3049. [[CrossRef](#)] [[PubMed](#)]
82. Ding, D.; Jiang, D.; Zhou, Y.; Xia, F.; Chen, Y.; Kong, L.; Wei, J.; Zhang, S.; Deng, S. Assessing the Environmental Impacts and Costs of Biochar and Monitored Natural Attenuation for Groundwater Heavily Contaminated with Volatile Organic Compounds. *Sci. Total Environ.* **2022**, *846*, 157316. [[CrossRef](#)] [[PubMed](#)]
83. Qiang, C.; Ni, X.; Wu, J.; Xu, F.; Liu, Y. Screening Method and Engineering Application of Combined Remediation Technology for Petrochemical Aggregation Sites Based on AHP-TOPSIS. *Environ. Eng.* **2025**, *43*, 211–222. [[CrossRef](#)]
84. Zhou, Q. The Cost of the Project of a Certain Soil and Groundwater Repair Project Research on the Whole Process. *Manag. Sci. Eng.* **2023**, *12*, 556–562. [[CrossRef](#)]
85. Federal Remediation Technologies Roundtable (FRTR). Soil Vapor Extraction and in Situ Chemical Oxidation at Swift Cleaners, Jacksonville, Florida. Case Studies Search. Available online: <https://www.frtr.gov/costperformance/profile.cfm?ID=404&CaseID=404> (accessed on 15 May 2026).

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