

Article

Multi-Objective Decision-Making Evaluation Method of Environmental Impact Associated with the Life Cycle of Agro-Friendly Biochar Materials

Shunyang Wang^{1,2} , Jing Wei^{1,*}, Hua Li³, Da Ding¹, Yaxin Zhang³, Yuen Zhu³, Shaopo Deng¹ and Yongming Luo^{2,*}

¹ Environmental Protection Key Laboratory of Soil Environmental Management and Pollution Control, Nanjing Institute of Environmental Sciences, Ministry of Ecology and Environment, Nanjing 210042, China; dingda@nies.org (D.D.)

² Institute of Soil Science, Chinese Academy of Sciences, Nanjing 210008, China

³ College of Environmental & Resource Sciences, Shanxi University, Taiyuan 030006, China

* Correspondence: jingwei_nies@foxmail.com (J.W.); ymluo@issas.ac.cn (Y.L.)

Abstract: The urgency of addressing farmland contamination is undeniable. However, the environmental impacts associated with soil remediation, especially during the production of remediation materials, are often overlooked. This study seeks to fill this gap by conducting a comprehensive environmental impact assessment of remediation material production processes. We apply a Life Cycle Assessment (LCA) framework, enhanced by a multi-objective optimization model combining the Analytic Hierarchy Process (AHP) and Techniques for Order Preference by Similarity to an Ideal Solution (TOPSIS). This method enables the integration of multiple environmental indicators into a high-dimensional reference system, reducing subjectivity in decision-making. The study focuses on the environmental impacts of 11 types of biochar materials used in soil remediation. Among these, alkali-modified biochar loaded with nano TiO₂ exhibited the highest environmental impact index. Sensitivity analysis further confirmed the robustness of the method, with impact variations ranging from 0.44 to 0.52, suggesting the model's reliability in comparing different remediation materials. Our findings highlight the significant environmental variability between remediation materials and underscore the necessity of incorporating comprehensive environmental assessments in material selection processes. This study provides a valuable framework for optimizing the environmental sustainability of soil remediation efforts.

Keywords: LCA; MCDM; AHP; TOPSIS; biochar materials; environmental impact



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1. Introduction

Under the rapid development of intensive agriculture, the soil contamination of agricultural land has intensified, especially in China. It poses a significant threat to crop safety and human health [1]. Zeng et al. conducted a comprehensive sampling and investigation of 1781 farmland soil sample plots across China. The findings revealed that grain and vegetable plantations exhibited the most significant heavy metal and organic contamination, with Cd contamination levels exceeding those of other pollutants, followed by PAHs. Additionally, the contamination in the southern regions was more pronounced than in the northern regions [2]. The contamination of agricultural soils can result in the contamination of foodstuffs, which, in turn, can pose a risk to human health. This risk is referred to as the soil–food–human chain. Studies have demonstrated that the consumption of crops grown in contaminated soil can result in the accumulation of pollutants in human bloodstream [3]. Therefore, the contamination of agricultural land has become a critical environmental issue that requires immediate attention and resolution [4]. In this context, there has been a research emphasis on developing soil remediation technologies and

materials that are efficient, cost-effective, and eco-friendly [5,6]. Soil remediation materials that are eco-friendly aim to achieve remediation goals with minimal environmental impact, both in the short and long term [7]. Rashid et al. [8] proposed the role of free radicals in biochar and its eco-friendly use in remediation materials. Biochar shows excellent potential for application in the remediation of arable land pollution, including carbon sequestration, pollution reduction, and yield enhancement in agricultural systems [9].

The Life Cycle Assessment (LCA) is a systematic method for evaluating the environmental impact of a product or process throughout its entire life cycle. An LCA was developed in the late 1960s and early 1970s. At present, the LCA method is a key focus in various countries and regions. Additionally, life cycle assessment systems have been rapidly developing in diverse industries throughout different countries [10]. In recent years, this method has been utilized to assess the eco-friendliness of various soil remediation materials and techniques. Hu et al. [11] evaluated the environmental impact of base-catalyzed decomposition (BCD) and infrared high-temperature incineration (IRI) in remediating polychlorinated biphenyl (PCB)-contaminated soil through the LCA method. The results showed that BCD and IRI technologies yielded environmental impact values of 0.147 and 0.279 Pt, respectively, in treating 1000 kg of PCB-contaminated soil. It provides a theoretical and data-driven foundation for optimizing the procedures of both technologies. Dong et al. [12] performed an LCA on sites contaminated with chromium that required remediation. Their findings revealed that the total secondary environmental impact resulting from the remediation projects amounted to 5.84×10^3 Pt, with human health damage, ecosystem damage, climate change, and resource consumption accounting for 45.63%, 7.28%, 24.13%, and 22.96% of the overall impact, respectively. Papageorgiou et al. [13] conducted an LCA to analyze the environmental impact of in situ and ex situ biochar remediation technology for soil contaminated with metal(loid)s and PAH. They discovered that waste wood biochar remediation outperformed traditional landfill methods in 10 to 12 environmental impact categories. Additionally, in situ remediation was more effective than the ex situ remediation. However, the above-mentioned LCA process compared various indicators without comprehensively evaluating the subjects. Therefore, decisions based on single-score indicators in LCA research have not always been justified [14]. Barbhuiya et al. [15] noted the subjective nature of the LCA evaluation process, where varying interpretations and weightings of environmental impacts might result in diverse conclusions and recommendations. The authors also stressed the importance of standardizing LCA methods and proposed the development of consensus-based solutions for impact categories, characterization models, and weighting factors for future implementation. Therefore, researchers explored alternative decision-making methods. Researchers often introduce multi-objective decision analysis methods to address complex problems, such as the "Analytic Hierarchy Process" (AHP), "Order Preference by Similarity to an Ideal Solution" (TOPSIS), "Information Entropy Method" (IEM) among others. To evaluate the adverse environmental effects of automotive components throughout their lifecycle and identify the most sustainable materials, Ma et al. [16] combined TOPSIS and IEM with LCA, evaluated the environmental impact of selecting automobile material, and identified the material with the least environmental impact out of 16 alternatives, demonstrating the effectiveness and robustness of the method. In order to determine the most effective acidification and modification program to enhance coalbed methane extraction in low-permeability conditions, He et al. [17] proposed the improved AHP-TOPSIS method to identify the most effective wettability modification parameters for determining the optimal acidification modification strategy among nine acidification modification plans. The combination of LCA and biochar remediation material provides further evidence of the efficacy of biochar. Amirahmadi et al. [18] investigated the impact of biochar, cow dung, and chemical fertilizer on the growth of sugar beet. Their findings demonstrated that the application of biochar not only enhanced the yield of sugar beet, but also reduced the global warming and eutrophication values by LCA. The environmental sustainability of biochar as a green adsorbent was discussed in the context of an LCA review by Osman et al. [19]. The article

shows that biochar has excellent soil decontamination capacity and significantly reduces climate change impacts. However, the article also mentions that future LCA assessments of biochar in soil still require improved data and modeling methods.

To assess the eco-friendliness of soil remediation materials in a scientific and impartial manner, it is crucial to standardize the traditional LCA. The multiple-criteria decision-making model (MCDM) combines the objectives that are examined across different dimensions into a vector. Conflicting objectives may be adjusted to the same scale using scientific normalization techniques applied via normalization methods. These provide a scientific and reasonable comparison to achieve optimal decision-making. Currently, there are several well-established MCDM methods in use, including the AHP [20], Simple Additive Weighted (SAW) [21], TOPSIS [22], Complex Proportional Assessment (COPRAS), and Weighted Product Method (WPM) [23,24]. The TOPSIS method has the advantages of flexibility, ease of calculation, and straightforward results, but the indicators in TOPSIS share the same magnitude order, which fails to reflect the importance level of each indicator. AHP, on the other hand, serves as a method to determine the weights of each indicator, assigning corresponding weights to the significance of each objective. Thus, the comprehensive evaluation method that is commonly employed is TOPSIS and the AHP. TOPSIS and the AHP are evaluation methods that complement each other by compensating for each other's strengths and weaknesses, resulting in a more holistic evaluation. The AHP is a subjective method, whereas TOPSIS is an objective one. The application of objective methods enables decision-makers to ascertain the relative importance of the criteria based on the characteristics of the options data, objectively. However, these objective methods do not reflect the preferences and wishes of decision makers. Therefore, subjective weighting methods, which reflect the views of stakeholders, are widely used to determine the weight [25]. Furthermore, AHP-TOPSIS has not been applied in the LCA for environmental impact assessment of soil remediation materials.

Therefore, this study established an "AHP-TOPSIS" multi-objective optimization model based on the traditional environmental impact assessment of the LCA for soil remediation materials. The methodology integrates various environmental impact indicators from the LCA and converts diverse LCA data into a reference point system in high-dimensional space. This approach rationalizes the significance of the indicators and reduces the subjectivity of the multi-objective decision-making process. Furthermore, tests were conducted to standardize several environmental impact indicators used in the traditional LCA of soil remediation materials, which led to the development of a comprehensive method for assessing environmental impact that is highly integrated and thorough. The evaluation model employed in this study can be used to examine the choice of agro-friendly remediation materials—biochar. It highlights the environmental impacts of preparing efficient remediation materials.

2. Materials and Methods

2.1. Construction of Assessment Methods

2.1.1. The Basic Idea of the Method Construction

During the remediation process, the environmental impact varies depending on the methods used for material preparation. Yang et al. [26] investigated various biochar preparation and modification methods. The author also evaluated the prospective environmental effects of biochar and noted in their paper that there was a lack of LCA studies on biochar. Belhachemi et al. [27] evaluated the NO₂ adsorption capabilities of date pits biochar activated physically and chemically and compared them with modified commercial activated biochar. The activated biochar treated differently exhibited a high capacity for adsorbing nitrogen dioxide. However, the environmental impacts of various preparation methods could vary, and this aspect of the impact was often overlooked.

In the above research, the environmental effects of the material preparation process were described primarily through textual narratives and data synthesis. Quantitative analysis of environmental impacts was not possible. Therefore, the LCA was chosen to

assess the ecological consequences of materials used during the preparation process. Based on the conventional LCA of soil remediation materials, the environmental impact indicators of these materials were optimized using multi-objective decision-making methods. These indicators were subsequently integrated to rank the environmental impacts, which include the following:

- The framework of the LCA for soil remediation materials

The basic framework of the LCA in the ISO 14040 [28] series can be summarized into four parts: (1) determination of goal and scope; (2) inventory analysis; (3) impact assessment; (4) interpretation of results.

- The ideas of the MCDM method construction

Firstly, the environmental impact assessment index for the LCA has been normalized and weighted. It is essential to allocate varying levels of significance to each indicator to ensure alignment between the environmental impacts in LCA and real-world conditions. At present, the AHP and entropy weight method (EWM) are the prevalent techniques for weight calculation. Although the EWM is considered more objective than the analytic hierarchy process, it cannot perform horizontal comparisons and may easily overlook crucial impact items, resulting in the underestimation of indicators with significant environmental impact values [29]. The AHP, a widely used method for multi-objective decision evaluation, is a flexible and straightforward approach that combines both qualitative and quantitative analysis. AHP integrates multi-objective decision-making with fuzzy mathematics theory to conduct both qualitative and quantitative analysis across multiple levels and indices. It simplifies intricate multi-objective decision-making problems through index scoring and optimizes scheme selection. Therefore, this study aimed to utilize the AHP approach for the distribution of weights.

Secondly, the study utilized the TOPSIS method to comprehensively rank environmental impacts based on indicators, after allocating weights to the indicators. Therefore, the AHP-TOPSIS method was created. In this method, the TOPSIS method can be used to evaluate both large and small samples with multiple indicators. The computation of TOPSIS is straightforward, and the outcomes are numerical and intuitive. The TOPSIS method yields solutions closest to the optimal hypothesis solution and farthest from the worst hypothesis solution. The TOPSIS method selects the best option with the shortest Euclidean distance from the positive ideal solution (PIS) and the longest Euclidean distance from the negative ideal solution (NIS). The PIS is the best set of values for all evaluation criteria, while the NIS is the worst value set for all evaluation criteria [30]. For criteria evaluating the effectiveness of remediation and the pollution removal rate, a higher attribute value is preferred. However, for criteria assessing environmental impact and cost, a smaller attribute value is ideal. The TOPSIS method creates an interval between the “positive ideal solution” and the “negative ideal solution”, and the optimal scheme arrangement is determined by comparing the targets’ Euclidean distance. In this study, this method focuses on assessing the impact indicators of remediation materials on soil through LCA evaluation. The study then quantifies the magnitude of environmental impact values by converting the “positive and negative ideal solution”. The maximum environmental impact value refers to the “positive ideal solution”, while the minimum point of the environment impact value refers to the “negative ideal solution”.

2.1.2. Construction Method

Analytical Hierarchy Process weighted LCA environmental impact indicators

(1) Constructing judgment matrix $A = \{a_{ij}\}$

The judgment matrix for evaluation is constructed using a judgment score based on the relative importance score obtained through a pairwise comparison of each indicator. To assess the relative importance of two LCA impact indicators, we construct an importance ratings matrix $A = \{a_{ij}\}$. The scoring standard is usually an odd number (1, 3, ..., 9) and its

even-numbered inverses (2, 4, . . . , 8), which represents the median value of the judgment. The scoring criteria are shown in Table S1 [31].

(2) Normalization

According to Equation (1), the score is normalized, and the weight of each index is obtained.

$$W_i = \frac{\sqrt[n]{\prod_{j=1}^n a_{ij}}}{\sum_{i=1}^n \sqrt[n]{\prod_{j=1}^n a_{ij}}} \quad (1)$$

where W_i is the weight vector of the evaluation index; a_{ij} is the importance score of indicator i and indicator j ; and n is the number of indicators.

The evaluating process of AHP-TOPSIS coupled with the LCA:

For different life cycle impact assessment (LCIA) methods, Dreyer et al. [32] conducted a comparison. They cited three common LCIA methods: EDIP97, CML2001, and Eco-indicator 99. CML2001 is based on an adaptation of an integrated multi-media model developed for chemical risk assessment.

In this study, the positive and negative ideal points of TOPSIS were set as the maximum and minimum environmental impact points. The standardized weights of the above indicators were incorporated into the environmental impact indicators in the CML model of the LCA to assess the environmental impact values resulting from the material preparation process. The calculation process of TOPSIS is as follows:

(1) Constructing judgment Matrix

After completing boundary determination and inventory data collection, relevant data are imported into the CML model of the GaBi (10.6.2.9) software to calculate Acidification Potential (AP), Eutrophication Potential (EP), and other indicators. This process generates the environmental impact characteristic values for the remediation material preparation process and constructs the decision matrix $E = \{e_{ij}\}_{m \times n}$.

(2) Matrix normalization

Equation (2) normalizes the above matrix and generates the decision matrix $Z = \{z_{ij}\}$. This standardizes the original data, converting all the index data to the same scale, facilitating comprehensive comparison and evaluation.

$$z_{ij} = \frac{e_{ij}}{\sqrt{\sum_{i=1}^n e_{ij}^2}} \quad (2)$$

where z_{ij} is the normalized value of the i th evaluation object under the j th indicator; e_{ij} is the environmental impact characteristic value of the i th evaluation object under the j th indicator; and n is the number of indicators.

(3) Weighting by Analytic Hierarchy Process (AHP)

To construct the weighted normalization matrix $X = \{x_{ij}\}$, the weight $W = [W_1, W_2, W_3 \dots W_n]$ calculated using the AHP method must be utilized. Then, the weight of each indicator should be incorporated into the matrix to allocate the significance of each environmental impact.

$$x_{ij} = w_j \cdot z_{ij} \quad (3)$$

$$X = \begin{bmatrix} x_{11} & \dots & x_{1n} \\ \dots & \dots & \dots \\ x_{m1} & \dots & x_{mn} \end{bmatrix}$$

where x_{ij} is the weighted normalization value of the i th evaluation object under the j th indicator; z_{ij} is the normalized value of the i th evaluation object under the j th indicator; w_j is the importance value of the j th indicator.

(4) The Euclidean distance calculation between each point and the reference point in TOPSIS

The maximum and minimum environmental impact value schemes are determined using Equation (4) of the environmental impact matrix. The scheme with the maximum environmental impact value is $A^+ = \{x_1^+, x_2^+, x_3^+, \dots, x_n^+\}$, and the scheme with the minimum environmental impact value is $A^- = \{x_1^-, x_2^-, x_3^-, \dots, x_n^-\}$.

The synthetic calculation of the Euclidean distance between the potential value of each environmental impact and the ideal scheme is performed.

$$d_i^+ = \sqrt{\sum_{j=1}^n (x_{ij} - x_j^+)^2} \quad d_i^- = \sqrt{\sum_{j=1}^n (x_{ij} - x_j^-)^2} \tag{4}$$

where x_i^+ is the maximum weighted normalization value under the j th indicator; x_i^- is the minimum weighted normalization value under the j th indicator; d_i^+ is the Euclidean distance to the maximum point of the environment impact value; d_i^- is the Euclidean distance to the minimum point of the environment impact value.

(5) Calculation of relative proximity by TOPSIS

Equation (5) is utilized for computing the comprehensive evaluation index, which denotes the relative proximity and enhances the ranking's intuitiveness.

$$\Delta_i = \frac{d_i^-}{d_i^- + d_i^+} \tag{5}$$

where Δ_i is the comprehensive evaluation index of the i th object; d_i^+ is the Euclidean distance to the maximum point of the environment impact value; d_i^- is the Euclidean distance to the minimum point of the environment impact value.

According to Δ , the scheme with the largest environmental impact is ranked first, and the later in the ranking, the smaller the environmental impact value of the material.

(6) Sensitivity analysis

Sensitivity analysis can be utilized to validate the AHP-TOPSIS model's uncertainty. The stability of the AHP-TOPSIS approach is demonstrated if changes in the collected data have minimal impact on the final outcomes. If data volatility is more likely to cause changes in ranking results, it suggests that the determined evaluation method is highly sensitive to the final outcomes. Data variations and attribute weights are the primary factors that significantly impact the final results in this study. Eventually, changes in data can lead to changes in attribute weights. To determine the sensitivity of the method, the error transfer equation based on the judgment matrix of the TOPSIS method is introduced.

The sensitivity calculation involves introducing the normalized matrix $\{Z_{ij}\}$ and weighted decision matrix $\{X_{ij}\}$ into the error transfer Equation (6), and then using the computed results in the calculation Equation (7) for the comprehensive evaluation index. The uncertainty in this method is $\Delta U_i / U_i$ [33].

$$\Delta U_i = \sqrt{\sum_{j=1}^n (w_j)^2 (z_{ij})^2} \tag{6}$$

$$U_i = \sum_{i=1}^n x_{ij} \tag{7}$$

where ΔU_i is the error transfer equation; w_j is the weight of the j th indicators; z_{ij} is the normalized value of the i th evaluation object under the j th indicator; U_i is the comprehensive evaluation value of the i th object.

2.2. Applications

To examine the practicability and soundness of the “AHP-TOPSIS” methodology devised in this study, 11 biochar materials were selected as the subjects of the study. First, the “traditional LCA + AHP-TOPSIS” evaluation was conducted to confirm the method’s practicability. Then, the evaluation results and sensitivity were examined to demonstrate its rationality, stability, and applicability.

2.2.1. Determination of Research Objectives and Scope

Biochar is a carbonaceous and porous material created through the process of high-temperature pyrolysis of biomass. Its highly aromatic properties make it an insoluble substance with a high specific surface area, enriched with carbon and numerous oxygen-containing functional groups such as -OH and -COOH [34]. The exceptional ability of biochar to bind, retain, and adsorb makes it a frequently utilized substance for eliminating different types of pollutants. Biochar has proven to be an excellent material for remediation purposes in wastewater treatment, emission control, and soil remediation. To enhance remediation efficiency, numerous biochar modification methods have been developed, such as acid modification, steam modification, and metal modification, among others. These modifications, developed by researchers, have effectively enhanced remediation efficiency [35].

The biochar feedstock utilized in this study was procured from willow branches situated on the university campus in Taiyuan, China. Following the washing, drying, crushing, and sieving of the biomass feedstock, the willow biomass was obtained. The resulting biochar was made into a carrier by firing willow biomass at 300 °C, 500 °C, and 700 °C, labeled as BC-300 °C, BC-500 °C, and BC-700 °C. To increase the adsorption performance of biochar, we chose to activate it by chemical methods, and the biochar (BC-700 °C) was subjected to pickling with HCl and alkaline washing with NaOH, labeled as HCl-BC and NaOH-BC.

Additionally, nano zero-valent iron (nZVI) and nano TiO₂ were separately introduced to the biochar before (BC-700 °C) and after treatment (HCl-BC/NaOH-BC). The nZVI particles were prepared using the liquid-phase reduction method [36], while nano TiO₂ particles were prepared using the sol-gel method [37]. The biochar loaded with nano zero-valent iron was labeled as BC-nZVI, the acid-modified biochar loaded with nZVI labeled as BC-HCl-nZVI, and the alkali-modified biochar loaded with nZVI labeled as BC-NaOH-nZVI. And the biochar loaded with nano TiO₂ was labeled as BC-TiO₂, the acid-modified biochar loaded nano TiO₂ labeled as BC-HCl-TiO₂, and the alkali-modified biochar loaded with nano TiO₂ labeled as BC-NaOH-TiO₂.

In summary, the 11 biochar materials were prepared.

The system boundary for the LCA comprised the stages of raw material collection, pretreatment, and biochar material preparation. The acquisition of biomass raw materials (branches) marked the starting point for the system boundary, accounting for the input and output of materials and energy during the cleaning, drying, slow pyrolysis, grinding, pickling, and nanomaterial loading processes. The study’s boundary was restricted to the laboratory preparation phase and excluded the transportation of materials, application to the soil, and recycling process. The system boundary is shown in Figure 1.

2.2.2. Inventory Analysis

This study used data on the production of biomass biochar and its modified materials, conducted by our research group. The raw material used for the production was biomass. The study’s functional unit was 100 g of biochar. The inputs included water (freshwater), electricity (coal-fired power generation), gas (N₂), and chemical agents such as polyethylene

glycol and concentrated hydrochloric acid. The outputs included wastewater and waste heat. The details are shown in Table S2 of the Supplementary Information file.

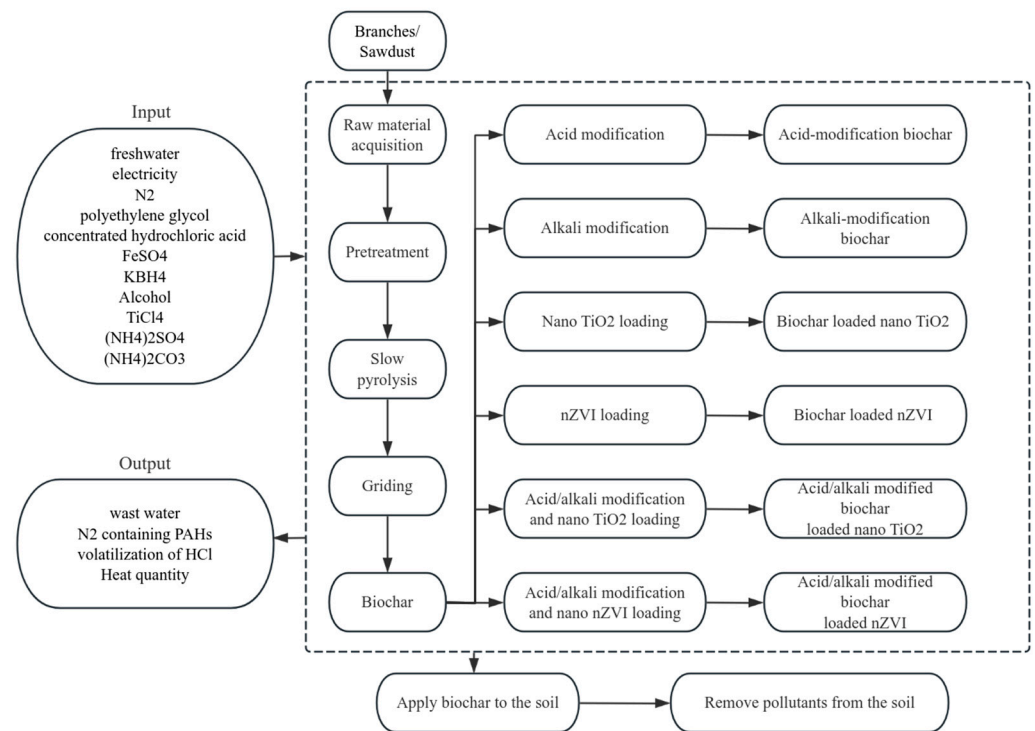


Figure 1. Diagram of the system boundary.

2.2.3. Index Selection

This study utilized the standardized calculations of the CML2001 characterization model to perform an environmental impact assessment on inventory data. The characteristics of environmental remediation materials necessitated the use of seven life cycle impact assessment (LCIA) indicators: acidification potential (AP), eutrophication potential (EP), global warming potential (GWP), ozone depletion potential (ODP), human toxicity potential (HTP), terrestrial ecotoxicity potential (TAETP), and abiotic depletion potential (ADP). For midpoint approaches like CML2001, different LCIA methods exhibit similar impact patterns, especially for energy-related impact categories like AP, EP, GWP, ODP, and ADP. For indicators of human toxicity or ecosystem toxicity, such as HTP and TAETP, the CML2001 score is dominated by contribution from metals [31]. This also demonstrates the appropriateness of selecting CML2001 in this study.

Figure 2 shows the distribution of each substance in the inventory data under the seven indicators.

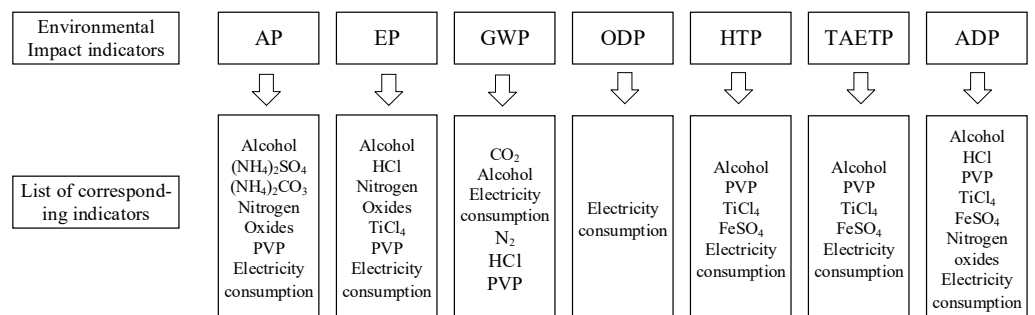


Figure 2. Classification of data indicators.

3. Results

3.1. Impact Assessment

Life cycle flow charts were established using GaBi (10.6.2.9) software in this study. We used its database of organics and building materials for input–output modeling. GaBi (10.6.2.9) software was utilized to carry out the LCA of biochar, while AHP-TOPSIS was employed for ranking and selecting the materials.

The assessment of the potential environmental impact of various materials is illustrated in Figure 3.

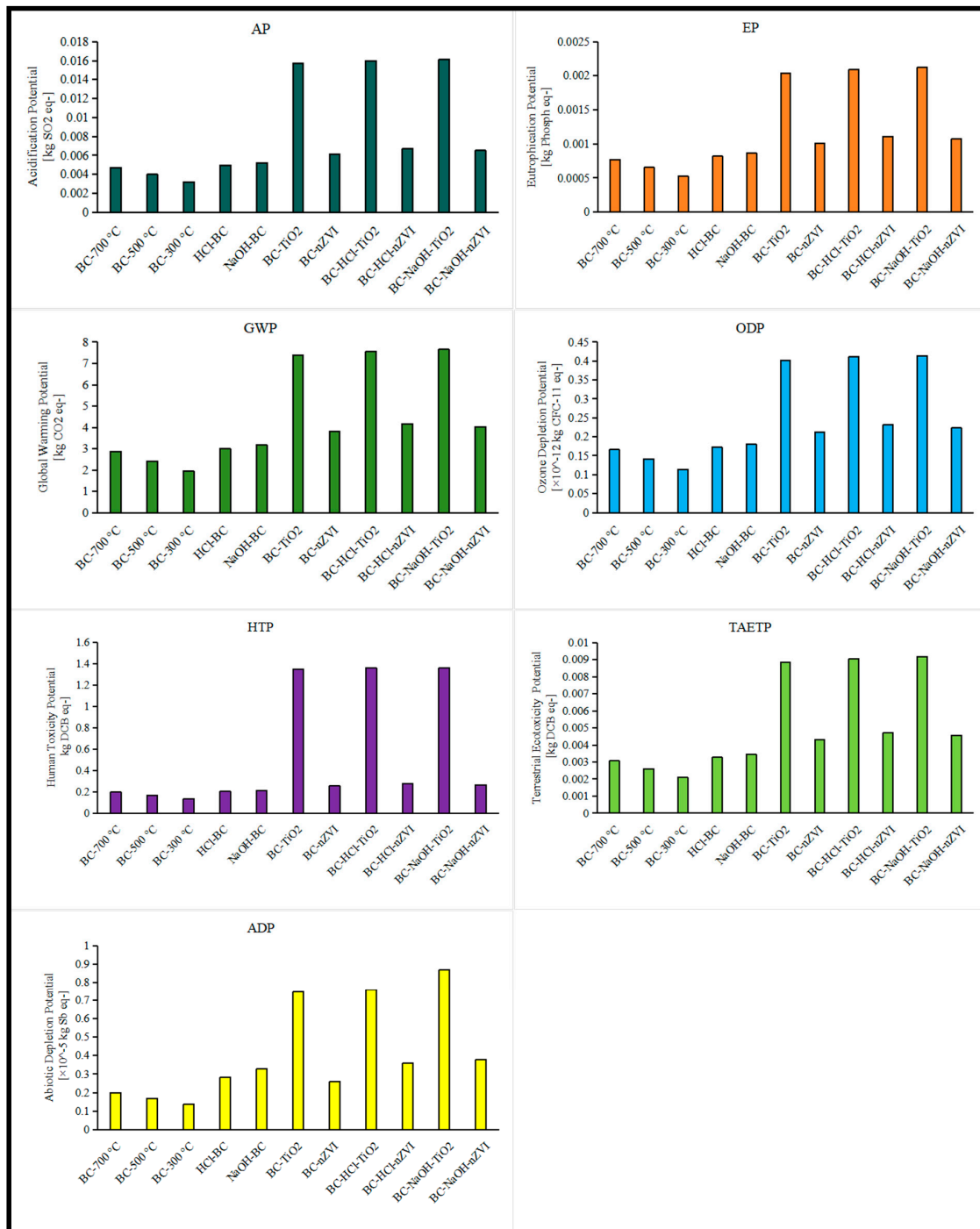


Figure 3. Evaluation results of environmental impact potential for each material.

Of all the materials, the modified material had a higher environmental impact value across all indices. Nevertheless, the use of multiple indicators made it challenging to draw comparisons between materials based solely on their environmental impact values. This was due to potential discrepancies in the environmental impact values of different indicators. Therefore, it was essential to perform a comprehensive assessment using AHP-TOPSIS. The TOPSIS method was utilized for a comprehensive evaluation of materials' environmental impact, as shown in Table 1.

Table 1. Evaluation results of environmental impact potential for different materials.

	AP	EP	GWP	ODP	HTP	TAETP	ADP
BC-700 °C	0.00471	0.00077	2.86	0.166×10^{-12}	0.195	0.00307	0.199×10^{-5}
BC-500 °C	0.00398	0.000652	2.42	0.141×10^{-12}	0.165	0.0026	0.169×10^{-5}
BC-300 °C	0.00319	0.000525	1.95	0.114×10^{-12}	0.132	0.0021	0.137×10^{-5}
HCl-BC	0.00496	0.000816	3	0.172×10^{-12}	0.202	0.00327	0.283×10^{-5}
NaOH-BC	0.00523	0.000862	3.17	0.181×10^{-12}	0.212	0.00344	0.329×10^{-5}
BC-TiO ₂	0.0157	0.00204	7.39	0.401×10^{-12}	1.35	0.00886	0.746×10^{-5}
BC-nZVI	0.00615	0.00101	3.82	0.213×10^{-12}	0.254	0.0043	0.259×10^{-5}
BC-HCl-TiO ₂	0.016	0.00209	7.55	0.411×10^{-12}	1.36	0.00903	0.758×10^{-5}
BC-HCl-nZVI	0.00672	0.00111	4.17	0.232×10^{-12}	0.276	0.00472	0.359×10^{-5}
BC-NaOH-TiO ₂	0.0161	0.00212	7.65	0.414×10^{-12}	1.36	0.00917	0.868×10^{-5}
BC-NaOH-nZVI	0.00651	0.00107	4.03	0.223×10^{-12}	0.265	0.00456	0.378×10^{-5}

The decision matrix S1 and normalized decision matrix S2 are shown in the Supplementary Information. The scores used in this study relied on Tian et al.'s [38] research on the weighting of environmental impact indicators in the LCA as a reference standard, and the scores reflect the relative importance of selected indicators. The selected scores were derived from a rating index filled out by experts (Table 2).

Table 2. Scoring data of weights for environmental impact indicators.

	AP	EP	GWP	ODP	HTP	TAETP	ADP
AP	1	1	1/5	1/4	1/6	1/5	3
EP	1	1	¼	1/4	1/6	1/5	4
GWP	5	4	1	2	1/3	1/2	5
ODP	4	4	½	1	1/4	1/3	4
HTP	6	6	3	4	1	2	8
TAETP	5	5	2	3	1/2	1	7
ADP	1/3	1/4	1/5	1/4	1/8	1/7	1

The weight values of AP, EP, GWP, ODP, HTP, TAETP, and ADP were calculated according to the AHP. Their weight values were 0.047, 0.050, 0.165, 0.115, 0.353, 0.244, and 0.026, respectively. In addition, the consistency index was calculated by Equation (8).

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (8)$$

If $CR = CI/RI < 0.1$, it would pass the consistency inspection (RI values in Table S3). In this paper, the CR value was 0.05, the ratio of 0.064 to 1.35, which was smaller than 0.1. Therefore, it conformed to the consistency inspection.

After we obtained the weight values, the importance of each indicator was allocated as showed in Matrix S3 in the Supplementary Information.

The schemes with the greatest and the least environmental impact were determined as follows:

$$X_j^+ = [0.024, 0.024, 0.079, 0.054, 0.235, 0.120, 0.014]$$

$$X_j^- = [0.005, 0.006, 0.020, 0.015, 0.023, 0.028, 0.002]$$

Equation (4) was used to calculate the Euclidean distance in each selected scheme and the ideal scheme. The results are shown in Table 3.

Table 3. Ranking of environmental impacts and sensitivity analysis of different materials.

Remediation Materials	d_i^+	d_i^-	Δ_i	rank	U_i	ΔU_i	Sensitivity
BC-700 °C	0.2253	0.0209	0.0849	9	0.146	0.065	0.445
BC-500 °C	0.2343	0.0100	0.0410	10	0.121	0.055	0.455
BC-300 °C	0.2434	0	0	11	0.099	0.044	0.444
HCl-BC	0.2231	0.0240	0.0970	8	0.153	0.068	0.444
NaOH-BC	0.2199	0.0277	0.1119	7	0.162	0.072	0.444
BC-TiO ₂	0.0117	0.2389	0.9533	3	0.535	0.278	0.520
BC-nZVI	0.2081	0.0426	0.1699	6	0.192	0.087	0.455
BC-HCl-TiO ₂	0.003	0.2423	0.9878	2	0.545	0.282	0.517
BC-HCl-nZVI	0.2017	0.0483	0.1932	5	0.211	0.096	0.453
BC-NaOH-TiO ₂	0	0.2434	1.0000	1	0.550	0.283	0.515
BC-NaOH-nZVI	0.1993	0.0481	0.1944	4	0.205	0.092	0.449

The environmental impacts of various materials were ranked based on the relative approach degree. The results are also shown in Table 3.

In summary, the following results could be obtained based on seven evaluation indexes: AP, EP, GWP, ODP, HTP, TAETP, and ADP. On the scale of environmental impact assessment, a value of 1 represents the greatest impact, while a value of 0 indicates the least impact. The preparation of BC-NaOH-TiO₂ resulted in the highest environmental impact, as indicated by a comprehensive assessment index of 1. The comprehensive assessment of the environmental impact resulting from the production of BC-HCl-TiO₂ yielded a score of 0.9878, ranking second. However, the use of nano zero-valent iron as a substitute for nano TiO₂ resulted in a 0.8 reduction in environmental impact value. The environmental effects of pickling biochar and alkaline biochar followed closely. The comprehensive environmental impact index of the pickling material was 0.001–0.02 lower than that of alkaline biochar. The least environmental impact was pyrolyzed biochar, and its environmental impact value increased with elevated pyrolysis temperature.

3.2. Sensitivity Analysis

The sensitivities of the comprehensive evaluation of environmental impact values of various materials obtained with this method are shown in Table 3.

Using different values as a background, the sensitivities of multiple evaluation materials were calculated using the error transfer equation. The results indicated that sensitivities changed slightly, with fluctuations ranging from 0.44 to 0.52, demonstrating the stability of the AHP-TOPSIS method. The sensitivity of the nano-titanium-loaded material was 0.52, higher than the other materials, which had a sensitivity of 0.45. Due to the high environmental impact of the nano-titanium-loaded material, there were greater data losses compared to other materials during the process of normalization.

4. Discussion

In this study, the AHP-TOPSIS method was employed to determine the overall environmental effects of biochar and its modified materials. The environmental impacts were first calculated using GaBi (10.6.2.9) software. Then, the decision matrix was used for material comparison and selection. The method transformed the LCA evaluation under multiple indicators into a ranking evaluation based on the comprehensive index. It reasonably allocated the importance of each index, avoided strong subjectivity in the decision-making process, and expressed the results of the comparison results through numerical ranking for intuitive understanding.

The study indicates that the largest environmental impacts were in the alkaline biochar modified by nano TiO₂ (BC-NaOH-TiO₂), pickling biochar modified by nano TiO₂ (BC-HCl-TiO₂), and biochar modified by nano TiO₂ (BC-TiO₂). Many reports have mentioned the efficient remediation efficiency of biochar-TiO₂ compared to single biochar [39,40]. When TiO₂ was applied onto the biochar surface, and the external environment was exposed to ultraviolet light with a certain intensity, and the energy received by TiO₂ surpassed the bandgap threshold. As a result, the electrons were displaced, leading to the development of highly active photoactivated electrons (e⁻) and holes (h⁺). When photogenerated carriers reached the surface of TiO₂, they initiated a series of reactions with absorbed O₂, OH⁻, H₂O, and other molecules. These reactions could oxidize H₂O and OH⁻ molecules adsorbed on the surface of TiO₂ to ·OH, leading to increased photodegradation efficiency of pollutants [41]. Pickling and alkaline washing could clear the pores of the biochar and enhance the loading capacity. The environmental impact of remediation materials modified by nano zero-valent iron (nZVI) ranked as BC-NaOH-nZVI > BC-HCl-nZVI > BC-nZVI. This modification method could employ the robust reducibility of nano-iron to achieve a more potent reduction and stabilization of pollutants compared to biochar [42,43]. Compared to nano-titanium material, the efficacy of nano-iron material for remediation varies depending on the pollutants [44]. In general, titanium dioxide-modified materials demonstrate superior remediation efficacy for most organic pollutants compared to nano-iron-modified and pure biochar materials [45,46]. The study results indicated that the biochar materials modified by nano zero-valent iron had a lower environmental impact compared to TiO₂-modified materials, suggesting an inconsistency between the remediation effect and environmental impact. The environmental impact of alkaline biochar was marginally lower than that of pickling biochar, but the difference was not significant, so a single acid-base modification had similar environmental effects. Furthermore, the environmental impact value resulting from the calcination process of biochar escalated as the calcination temperature (BC-700 °C > BC-500 °C > BC-300 °C) because higher temperatures required more energy consumption and increased the environmental impact.

Biochar and nanoparticle-decorated biochar are high-performance functional materials. The various modification methods could enhance the remediation efficiency of biochar materials. This not only benefits the regeneration of the catalyst but also mitigates the disadvantage of swift depletion, difficult separation, and retrieval of TiO₂ and nano-iron powder. It also enhances the surface area of TiO₂ and Fe, improving the reaction efficiency of TiO₂ photocatalysis and nano-iron [47]. Therefore, it is important to integrate environmental sustainability and human health objectives into the selection and design processes of biochar and nanoparticle-decorated biochar [48]. The use of LCA to support decision-making in the development of innovative, healthy products is critical to the selection of environmentally friendly products [49].

This study reveals that nano-metal-modified biochar positively impacted the remediation of contaminated soil. However, the preparation process of these materials had a significantly greater environmental impact than other materials. The order of environmental impact showed that supported nano titanium dioxide had a significantly higher impact than supported nano zero-valent iron. Pickling and alkaline biochar enhanced remediation effectiveness but came with an increased environmental impact. According to the LCA, the environmental impact value of the modified biochar preparation process increased under each index, especially in the categories of GWP and HTP. Therefore, improving the effectiveness of remediation materials resulted in a corresponding environmental burden. To maximize the benefits for both remediation and the environment, it was necessary to regulate the environmental impact while choosing appropriate remediation materials. In upcoming research, the raw materials for the preparation process could be optimized to select a method that minimizes environmental impact.

In summary, though modifying remediation materials improved the remediation effect, it ultimately reduced environmental benefits throughout the entire life cycle. Therefore, considering only the remediation effect and environmental benefits was insufficient for

achieving optimal comprehensive benefits. Therefore, the “AHP-TOPSIS” method of multi-objective decision-making demonstrated high reliability and practicality. The sensitivity analysis model showed that the sensitivities fluctuated between 0.44 and 0.52 without any significant changes, indicating the method’s high stability.

5. Conclusions

Biochar and its derivatives have demonstrated significant potential in the remediation of farmland contamination, showing excellent remediation effects. However, the environmental impacts associated with their preparation processes remain a concern. In this study, 11 biochar materials were ranked based on their environmental impact, with the order from largest to smallest being BC-NaOH-TiO₂ > BC-HCl-TiO₂ > BC-TiO₂ > BC-NaOH-nZVI > BC-HCl-nZVI > BC-nZVI > NaOH-BC > HCl-BC > BC-700 °C > BC-500 °C > BC-300 °C. Although various modification methods improve remediation efficiency, the results from the Life Cycle Assessment (LCA) showed that these enhancements come at the cost of environmental benefits. The “AHP-TOPSIS” method developed in this study proves to be a reliable, practical, and stable tool for optimizing the selection of soil remediation materials, offering a comprehensive approach to minimize the subjectivity of traditional methods like the LCA and AHP while preventing the neglect of weights in TOPSIS. This integrated approach presents a valuable framework for enhancing the environmental sustainability of soil remediation strategies, with significant potential for multi-objective decision-making.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/agronomy14112583/s1>, Table S1: The scoring basis for the importance of indicators in AHP; Table S2: List of biochar and modified materials; Table S3: RI value corresponding to matrix order; Matrix S1: Constructed decision matrix; Matrix S2: Normalized decision matrix; Matrix S3: Weighted normalization matrix.

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