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Original Research

Evaluation of Biochar for Pollutant Adsorption by Analytical Methods

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Abstract

The aim of this study is to objectively evaluate the adsorption performance of biochar. The performances of various biochars in adsorbing pollutants were thoroughly evaluated and compared using a combination of Analytical Hierarchy Process (AHP) and Grey Relational Analysis (GRA). The importance rankings of adsorption amount, adsorption time, and specific surface area in adsorption performance were determined through AHP, and the weights of each index were calculated to ensure consistency. Utilizing GRA, the degree of correlation between specific surface area, adsorption time, and adsorption performance was assessed, with adsorption amount as the reference value, which further validated the AHP results. The results show that adsorption capacity holds the highest weight at 64.83%, followed by adsorption time at 22.97%, and specific surface area at 12.20%, based on the AHP analysis. The GRA further confirms a stronger correlation between adsorption time and adsorption capacity, highlighting the greater influence of adsorption time on adsorption performance compared to specific surface area. These findings offer crucial guidance for applying biochar in environmental management, enhancing pollutant removal processes, optimizing material choices, and supporting environmental protection and sustainable development initiatives.

Keywords: adsorb heavy metals, analytic hierarchy process, biochar, grey relational analysis, waste biomasses

Introduction

Biochar is a porous, carbonaceous material produced through the pyrolysis or gasification of biomass under anaerobic conditions. It is characterized by an abundant microporous structure and extensive specific surface area [1, 2]. These characteristics endow biochar with excellent adsorption capabilities, allowing it to effectively adsorb pollutants [3], improve soil quality [4], purify water [5], and provide benefits in various other applications [6]. With the increasing severity of environmental pollution, the demand for efficient, economical, and environmentally friendly treatment methods is becoming increasingly urgent. Therefore, biochar has received widespread attention as a potential environmental treatment material. It plays a crucial role in promoting

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the sustainable treatment of Cd(II)-contaminated wastewater [7], acts as an adsorbent for the removal of microplastics and nanoplastics [8], and serves as a soil amendment and phosphate fertilizer for recovering phosphate from sludge incineration ash [9]. In today's field of environmental science, studying the types, properties, and adsorption mechanisms of biochar has become particularly important. Understanding the sources, preparation methods, and adsorption performance of various biochars is crucial for optimizing their preparation processes, enhancing their adsorption efficiency, and promoting their application in environmental management. By gaining a deeper understanding of the characteristics and applications of biochar, we can better utilize this material to address environmental issues and contribute to achieving sustainable development goals.

The Analytical Hierarchy Process (AHP) and Grey Relational Analysis (GRA) are two commonly used methods for evaluating adsorption efficiency [10, 11]. They possess distinct characteristics and advantages in analyzing the relationships and importance of various indicators in the adsorption process. The AHP hierarchizes various indicators and determines their weights by constructing a hierarchical structure and conducting pairwise comparisons. This approach enables a comprehensive evaluation of each factor [12, 13]. The AHP generates numerical priorities from subjective perceptions expressed in the comparison matrix through pairwise comparisons of relevant factors, facilitating both quantitative and qualitative judgments. It is applied widely in evaluating and analyzing policies concerning farmland protection, solid waste management, soil health assessment, environmental protection measures, and the assessment of heavy metal pollution in groundwater [14-16]. In the study of biochar adsorption of pollutants, the AHP method can be employed to determine the weights of indicators such as adsorption capacity, adsorption time, specific surface area, and adsorption efficiency. This allows for the comprehensive evaluation of the performance of different biochars. GRA, rooted in grey system theory, is another method used to assess the correlation between variables and identify factors significantly impacting adsorption efficiency [17-19]. In the study of biochar adsorption of pollutants, GRA can be utilized to explore the degree of correlation among factors such as adsorption time, adsorption capacity, and specific surface area, aiming to identify the key factors influencing adsorption efficiency. For instance, Sun et al. developed a multi-objective evaluation model integrating the AHP with GRA [20]. Arely et al. used the AHP method to demonstrate the strong adsorption capacity of Na jarosite adsorbent materials [21]. Wu et al. used GRA to evaluate the tar produced by microwave co-pyrolysis of low-grade coal and corn cob [22]. But in the field of biochar adsorption, there are not many studies on the combined use of these two models to evaluate the adsorption capacity of biochar. Therefore, by conducting in-depth analysis and evaluation of key performance indicators such as adsorption capacity, adsorption rate, selectivity, and regeneration capacity, we can better understand the applicability and advantages of different biochars in pollutant treatment. Given the increasing challenges of environmental pollution, there is an urgent need to determine effective and environmentally friendly treatment methods. Therefore, this study aims to provide a method for selecting a sustainable, economical, and environmentally friendly biochar, and to provide new solutions and insights for solving environmental pollution problems.

This study will conduct an in-depth evaluation and exploration of the performance of biochar derived from various biomass sources in adsorbing pollutants. The biomass materials involved include poultry bedding, canola seeds, wheat straw, corn cobs, waste peanut shells, and pine nut shells. The diversity of these raw materials offers a wide range of options for the preparation of biochar but also necessitates a more comprehensive and in-depth performance evaluation. This study will employ two evaluation methods (AHP and GRA) to comprehensively assess indicators such as adsorption capacity, adsorption time, and specific surface area. The aim is to objectively evaluate the adsorption performance of biochar, providing a scientific basis for optimizing its design and application.

Materials and Methods

Biochar Raw Materials

This article assesses the adsorption performance of various types of biochar derived from diverse biomass sources, each subjected to different preparation processes and conditions, thereby exhibiting distinct characteristics and specificity. The biomass materials involved include, but are not limited to, poultry bedding [23], canola seeds [24], wheat straw [25], corn cobs [26], waste peanut shells [27], and pine nut shells [28]. Here is a brief introduction to some of the biochars studied.

Poultry bedding biochar is derived from waste generated in poultry farming and is prepared through high-temperature pyrolysis or gasification. It possesses a porous structure and a significant specific surface area, making it highly effective for adsorbing organic pollutants [29]. Alfalfa sprout biochar, produced from alfalfa plant buds or straw, exhibits a rich carbon structure and porous morphology, contributing to its strong adsorption capacity for pollutants [30]. Waste peanut shell biochar, obtained through pyrolysis of discarded peanut shells, is characterized by a high specific surface area and porous structure, making it suitable for adsorbing heavy metals and other contaminants [31]. Pineapple shell biochar, derived from pine tree shells via pyrolysis or gasification, demonstrates a rich porous structure and effective adsorption performance, particularly for organic pollutants [32]. Corn cob biochar, derived from corn cobs through pyrolysis or gasification, features a porous structure and large specific surface area, effective for adsorbing organic matter and heavy metals in wastewater [33]. Potato skin biochar, obtained from the outer skin of edible potatoes through pyrolysis, exhibits a carbonaceous structure and porous nature, suitable for adsorbing organic matter and heavy metals [34].

The aforementioned biochars represent only a subset of those utilized in this study, each characterized by distinct preparation methods, physicochemical properties, and adsorption capabilities. Through comprehensive evaluation and comparison of these biochars, this research aims to provide a scientific foundation for optimizing their preparation processes and enhancing their practical applications.

Analytic Hierarchy Process

Principle

AHP, a method for multi-criteria decision-making, addresses intricate relationships among multiple levels and factors. It is frequently employed to assess decision-making challenges influenced by numerous factors [35-39]. The fundamental steps of AHP encompass constructing a hierarchical structure, forming a judgment matrix, computing weights, conducting consistency checks, and performing comprehensive evaluations [40]. AHP breaks down problems into constituent factors based on their nature and the overarching goal to be achieved. These factors are aggregated and organized across different levels according to their interrelationships, influences, and dependencies, forming a multi-level analytical structure model. Ultimately, AHP aims to determine the relative importance weights of the lowest level (such as solutions or measures for decision-making) relative to the highest level (the overall goal), or to establish the hierarchy of relative advantages and disadvantages [41].

Steps

(1) Establish a hierarchical structure model.

Top level (target level): the purpose of decision-making and the problem to be solved; Intermediate layer (criterion layer or indicator layer): the factors considered and the criteria for decision-making; the lowest level (scheme level): alternative solutions for decision-making.

(2) Construct a judgment (paired comparison) matrix.

A paired comparison matrix is a comparison that represents the relative importance of all factors in this layer against a certain factor (quasi side or target) in the previous layer. The element a_{ij} of the comparison matrix represents the comparison result of the i-th factor relative to the j-th factor. This value is given using Saaty's 1-9 scaling method, as shown in Table 1.

(3) The eigenvectors of the judgment matrix are determined to establish the approximate values using the square root method.

Table 1. 1-9 scaling method.

Relative importance	Definition
1	Equal importance
3	Marginally important
5	Considerable importance
7	Clearly important
9	Absolutely important
2,4,6,8	Intermediate values of two adjacent judgements
1/3	Slightly unimportant
1/5	Rather unimportant
1/7	Obviously not important
1/9	Absolutely nothing
1/2,1/4,1/6,1/8	Intermediate values of two adjacent judgements

Step 1: Calculate the n-th root of the product of elements in each row of the judgment matrix A, using the following formula:

$$M_{\mathrm{i}} = \sqrt[n]{\prod_{\mathrm{j}}^{\mathrm{n}} = 1\alpha_{\mathrm{ij}}} \tag{1}$$

Here, a_{ij} denotes the elements of matrix A, and n represents the number of elements in each row. This calculation aids in assessing the relative importance or preference between criteria or alternatives based on pairwise comparisons.

Step 2: Normalize M_i using the following formula:

$$W_{\mathrm{i}} = \frac{M_{\mathrm{i}}}{\sum_{\mathrm{i}=1}^{\mathrm{n}} M_{\mathrm{i}}} \tag{2}$$

Step 3: Calculate the maximum eigenvalue of the judgment matrix:

$$\lambda = \sum_{\mathrm{i}=1}^{\mathrm{n}} \frac{(A\omega)_{\mathrm{i}}}{\mathrm{n}\omega_{\mathrm{i}}} \tag{3}$$

(4) Verify the consistency of the judgment matrix.

C_I is the consistency indicator for measuring the deviation of the judgment matrix $C_I = (\lambda - n)/(n - 1)$. The larger the C_I, the worse the consistency of the judgment matrix. When C_I is 0, the judgment matrix has complete consistency. C_R is the consistency ratio. The formula is: $C_R = C_I/R_I$. Among them, RI is the average random consistency indicator, and when C_R<0.1, it can be considered that the consistency of the judgment matrix is acceptable.

Grey Relational Analysis

Principle

GRA was introduced by the Chinese scholar Chen in 1987 [42-44]. It is rooted in grey system theory and serves to examine the correlation among sequences, indicating their degree of similarity or correlation [45]. GRA processes and analyzes uncertain, incomplete, and partially known information to unveil relationships between variables and identify significant factors impacting the target variable. Not constrained by data distribution, GRA is particularly suitable for small sample datasets due to its ability to manage uncertainty and incompleteness [46].

Steps

(1) Determine the characteristic sequence and mother sequence. Compare sequences as:

$$\begin{bmatrix} X_1' & X_2' & \cdots & X_n' \end{bmatrix} = \begin{bmatrix} x_1'(1) & x_2'(1) & \cdots & x_n'(1) \\ x_1'(2) & x_2'(2) & \cdots & x_n'(2) \\ \vdots & \vdots & \cdots & \vdots \\ x_1'(m) & x_2'(m) & \cdots & x_n'(m) \end{bmatrix} \tag{4}$$

The mother sequence (i.e., evaluation criteria) is:

$$X_0' = \left(x_0'(1), x_0'(2), \cdots, x_0'(m)\right)^T \tag{5}$$

(2) To accurately represent real-world conditions and mitigate the influence of unit disparities and numerical magnitudes among indicators, it is essential to normalize the indicator data. SPSSPRO offers two methods for achieving dimensional consistency: initialization and averaging. These approaches ensure that data normalization is conducted effectively, thereby preventing anomalies in the analysis.

(3) Calculate the correlation coefficient.

Calculate the correlation coefficients between the corresponding elements of each comparison sequence and the reference sequence using the following Equations:

$$\gamma\left(x_0(k), x_i(k)\right) = \frac{\Delta \min + \rho \Delta \max}{\Delta_{ik} + \rho \Delta \max} \tag{6}$$

$$\Delta \min = \min_i \min_k \left| x_0(k) - x_i(k) \right| \tag{7}$$

$$\Delta \max = \max_i \max_k \left| x_0(k) - x_i(k) \right| \tag{8}$$

$$\Delta_{ik} = \left| x_0(k) - x_i(k) \right| \tag{9}$$

γ is the resolution coefficient, which takes a value within (0,1). The smaller the resolution coefficient, the greater the difference between correlation coefficients, and the stronger the discrimination ability, usually taken as 0.5.

(4) Calculate the correlation order.

Calculate the weighted average of the correlation coefficients between each indicator and the corresponding elements of the reference sequence, to reflect the correlation relationship between each manipulation device object and the reference sequence, and call it the correlation degree, denoted as:

$$r_{0i} = \frac{1}{m} \sum_{k=1}^{m} W_k \zeta_i(k) \tag{10}$$

(5) Analyze the calculation results. Establish the correlation order of each evaluation object based on the size of the grey weighted correlation degree. The greater the correlation, the greater the importance of the evaluation object to the evaluation criteria [47].

Results and Discussion

Different Adsorption Conditions of Biochar

Fig. 1 illustrates significant variations in the adsorption of different pollutants by various types of biochar. This variability is influenced by factors such as adsorption capacity, specific surface area, and adsorption duration.

Evaluation of Adsorption Capacity

The adsorption capacity directly quantifies the adsorption amount of pollutants that can be adsorbed per unit mass of biochar, serving as a primary indicator of its adsorption performance [48]. Under identical conditions, a higher adsorption capacity indicates a stronger adsorption capability of the biochar, resulting in more effective removal of pollutants. For instance, banana skin biochar exhibits remarkable adsorption capacity for lead, while potato skin exhibits excellent adsorption capacity in copper adsorption. Rice husk biochar demonstrates a notable adsorption capacity (125.34 mg/g) and possesses a high specific surface area (635 m^2/g) in cadmium adsorption [49]. In practical environmental governance applications, adsorption capacity serves as a pivotal criterion for evaluating the effectiveness of biochar's adsorption performance, carrying utmost significance. Hence, when selecting biochar as an environmental governance material, adsorption capacity emerges as the primary criterion for gauging its performance, determining the treatment

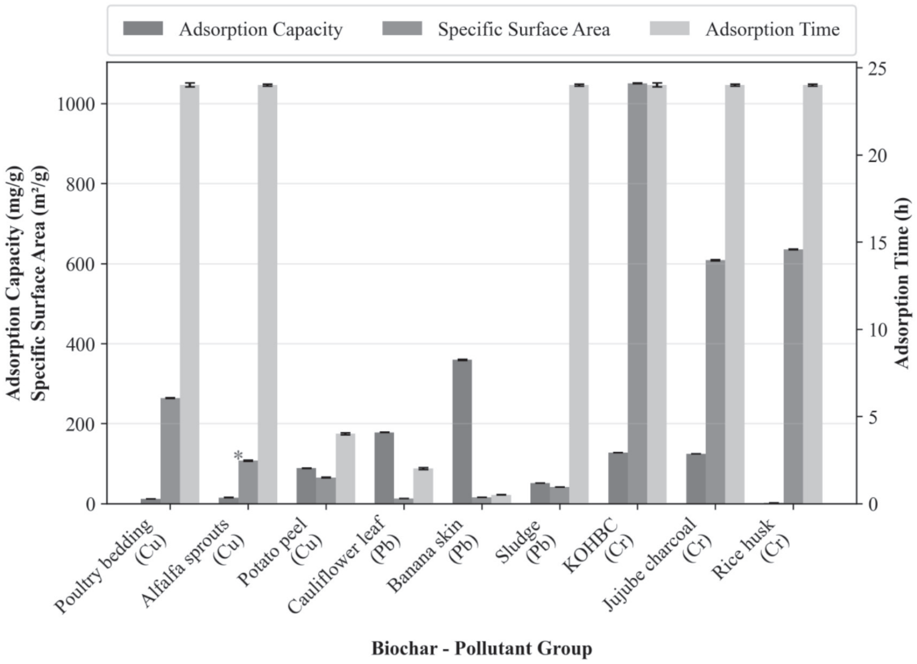

Fig. 1. Adsorption capacities of various biochars for different pollutants.

efficacy and economic benefits of biochar in practical applications.

Evaluation of Adsorption Time

The adsorption time signifies the duration required to attain adsorption equilibrium and is closely linked to the dynamic characteristics of the adsorption process [50]. Rapid achievement of adsorption equilibrium in practical environmental treatment enhances treatment efficiency, thereby reducing time and cost. For instance, banana peel biochar achieved a high adsorption capacity of 359 mg/g for Pb within just 0.5 hours, demonstrating rapid and effective adsorption capability [51]. Therefore, adsorption time is not only an important indicator for evaluating the adsorption performance of biochar but also one of the key factors to consider in practical environmental governance, emphasizing the significant impact of adsorption time on overall adsorption performance.

Evaluation of the Specific Surface Area

Moreover, the specific surface area denotes the quantity of adsorption sites available on the biochar surface. A larger specific surface area theoretically provides more adsorption sites, thereby enhancing adsorption capacity for pollutants [52]. The relationship between specific surface area and actual adsorption capacity is not strictly linear due to the influence of factors such as pore structure and surface chemical properties [53]. The pore structure of biochar is not well-developed, and the surface functional groups are limited, making it difficult to meet the efficient adsorption requirements for macromolecular pollutants. For instance, in the adsorption of Cu by sugar gum wood biochar, despite a high specific surface area of 429 m^2/g, the adsorption capacity of Cu on this biochar is only 7.41 mg/g, highlighting that other factors besides specific surface area affect adsorption levels [54]. Therefore, by subjecting biochar to secondary pore opening and pore expansion treatments, or modifying its surface through erosion, hydrolysis, and dehydration using chemical activators, its specific surface area and porosity can be significantly increased, while introducing a certain amount of active functional groups. These structural and chemical property optimizations help enhance the reactivity and mass transfer efficiency of biochar, thereby comprehensively improving its adsorption capacity for pollutants.

Impact of 3 Factors on Adsorption Performance

In evaluating adsorption performance, factors are prioritized as follows: adsorption capacity, which directly reflects biochar's ability to adsorb pollutants, is paramount; adsorption time determines the speed of achieving equilibrium, thereby impacting practical efficiency significantly; and specific surface area, while providing potential adsorption sites, has its actual impact influenced by various additional factors.

AHP Analysis Results

Indicator Index

Through systematic analysis of experimental data on the adsorption of pollutants by various biochar types, we identified the key factors affecting their adsorption performance and ranked their importance as follows: adsorption capacity (first), adsorption time (second), and specific surface area (third). Based on the 1-9 scale method proposed by Saaty, we constructed a judgment matrix as shown in Table 2 to further quantify the relative importance of each factor. This method compares the contributions of different factors to adsorption performance pairwise, transforming subjective judgments into a quantifiable numerical scale. The judgment matrix serves as the foundational input for the AHP, enabling a structured and mathematically rigorous approach to decision-making. This provides a basis for subsequent weight calculation in the AHP, ensuring that the evaluation process is both scientific and operable. The matrix not only reflects the dominant role of adsorption capacity in the evaluation of biochar performance but also clarifies the priority of different parameters in practical applications, providing theoretical support for optimizing the design and operating conditions of adsorbent materials. Furthermore, the consistency ratio (CR) of the matrix was calculated to validate the coherence of our pairwise comparisons, ensuring that the derived weights are reliable and logically sound.

AHP Results

The results of the AHP hierarchy analysis are shown in Table 3. The weight calculation results of the AHP show that the weight of adsorption amount is 64.83%, the weight of adsorption time is 22.97%, and the weight of specific surface area is 12.20%. From this, it can be preliminarily inferred that adsorption capacity is a key criterion for evaluating the effectiveness of adsorption performance.

Consistency Test Results

The consistency test results are shown in Fig. 2. According to the AHP calculation results, the maximum eigenvalue obtained is 3.004. Referring to the Random Index (R_I) table, the corresponding R_I value is 0.525. Thus, the Consistency Ratio (C_R), calculated as $C_R = C_I / R_I = 0.004$, is less than 0.1, indicating that the matrix passes the consistency test successfully. Among the indicators evaluated, adsorption capacity emerges as the most crucial, with a weight of 64.83%. This underscores the priority that should be given to adsorption capacity in decision-making processes. Adsorption time follows with a weight of 22.965%, indicating its significant but lesser importance compared to the adsorption capacity. Specific surface area holds the lowest weight at 12.20%, emphasizing its comparatively minor role in the decision-making context. The consistency test results confirm the reliability of the weight calculations, with a C_R value of 0.004, suggesting good consistency in the judgment matrix.

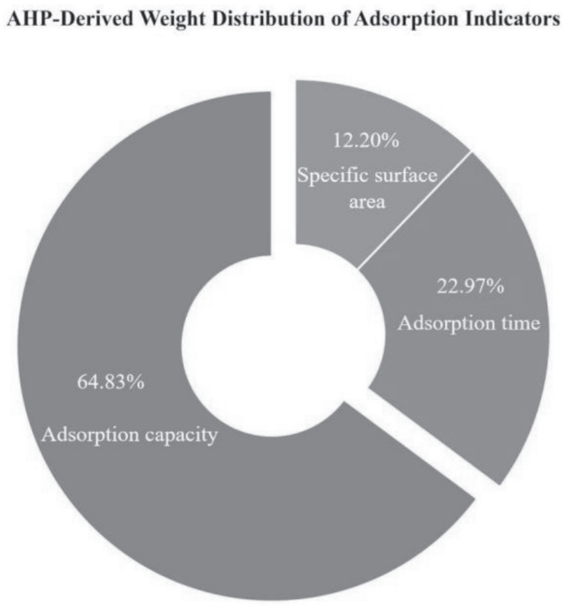

Fig. 2. Adsorption capacities of various biochars for Cu(II), Pb(II), and Cr(VI).

Table 2. Index matrix.

Norm	Adsorption capacity (mg/g)	Adsorption time (h)	Specific surface area (m^2/g)
Adsorption capacity (mg/g)	1	3	5
Adsorption time (h)	0.333	1	2
Specific surface area (m^2/g)	0.2	0.5	1

Table 3. Consistency test results.

Maximum characteristic root	C_I value	R_I value	C_R value	Consistency test results
3.004	0.002	0.525	0.004	pass

GRA Results

Grey Correlation Coefficient

Fig. 3 presents the results of GRA conducted on two evaluation metrics – specific surface area and adsorption time (in hours) – using 18 data points, with adsorption amount (mg/g) serving as the reference value (parent sequence). The study aimed to assess the correlation between these metrics and the adsorption amount, providing analytical references based on the correlation degree. During the analysis, a resolution coefficient (ρ) of 0.5 was utilized. The resolution coefficient $\rho \in (0, \infty)$, where smaller values indicate higher resolution. Typically falling within the range (0, 1), the specific value of ρ depends on the context. For optimal resolution, $\rho \leq 0.5463$ is recommended, often set at ρ = 0.5 [55].

Correlation Coefficient Chart

The correlation coefficient indicates the strength of the relationship between the specific surface area, adsorption time (h), and their respective dimensions within the parent sequence (where a higher coefficient signifies a stronger correlation). Fig. 4 illustrates the relational data diagram. By analyzing the adsorption data of different biochars, the study found a significant positive correlation between specific surface area and adsorption capacity (r = 0.65-0.92). Of these biochars, Zn biochar exhibited the strongest positive correlation, which is attributed to the introduction of metal active sites during zinc modification, and this not only expands the specific surface area but also synergistically enhances the adsorption capacity. The correlation coefficient of sludge biochar is relatively low, possibly due to its high ash content, which blocks some pores and weakens the contribution of the specific surface area. Furthermore, adsorption time generally shows a negative correlation with adsorption capacity, indicating that efficient adsorption is more likely to be achieved when the adsorption rate is fast. This is particularly evident in grapefruit peel biochar (r = -0.68), which may be closely related to its abundant mesoporous structure and surface functional groups.

Grey Correlation Degree

Table 4 integrates the correlation coefficient results with weighted processing to derive the final correlation values, which are utilized to evaluate and rank the two evaluation metrics. The correlation values range from 0 to 1, with higher values indicating stronger correlation with the "reference value" (parent sequence), signifying higher evaluation. From the table, it is evident that adsorption time (h) receives the highest evaluation (correlation degree: 0.783), followed closely by specific surface area (correlation degree: 0.766). In grey correlation analysis, these metrics are assessed for their correlation with the parent sequence: adsorption time (h)

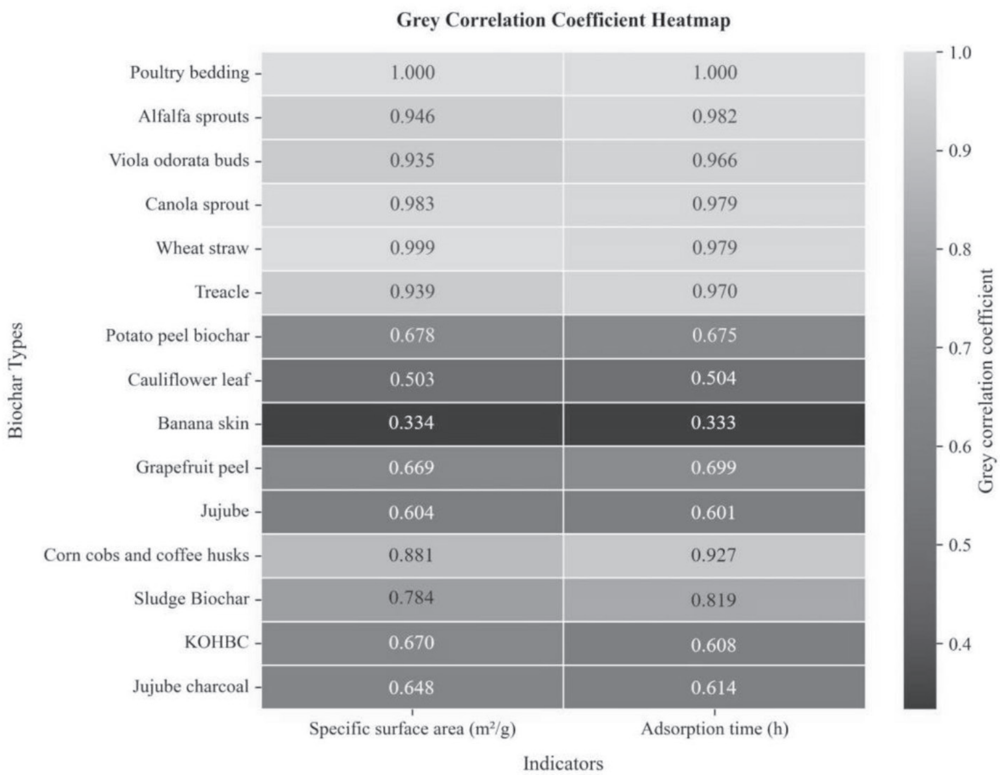

Fig. 3. Grey relational coefficient heatmap for specific surface area and adsorption time across eighteen biochar samples.

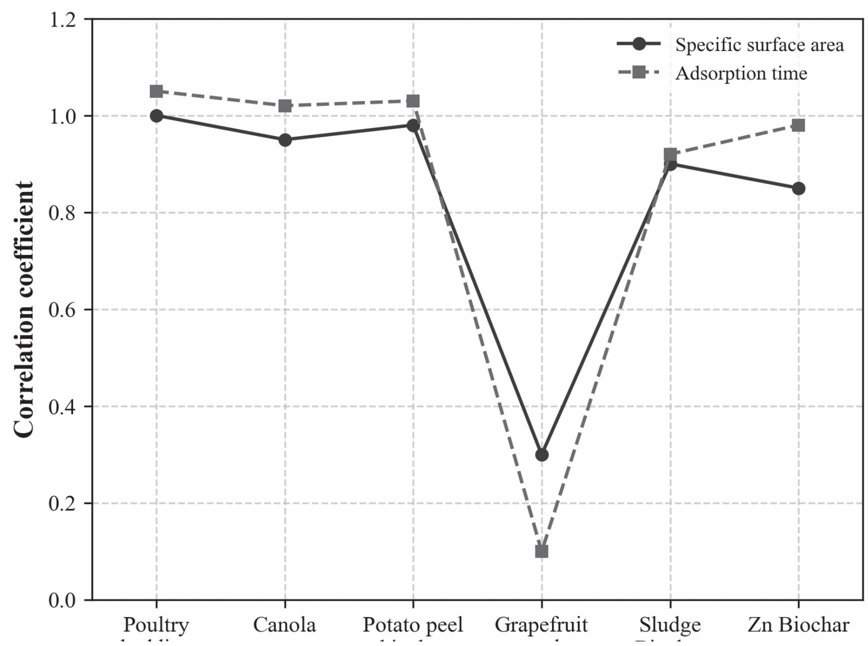

Fig. 4. Correlation coefficient.

shows a correlation of 0.783, whereas specific surface area exhibits a correlation of 0.766. Notably, adsorption time demonstrates a stronger correlation with adsorption amount compared to specific surface area.

Optimal Selection of Biochar

Based on the AHP analysis, adsorption capacity holds the highest weight at 64.83%, followed by adsorption time at 22.97%, and specific surface area at 12.20%. This weight distribution clarifies the relative importance of various factors in the adsorption process, with adsorption capacity as the core indicator guiding the evaluation of adsorption performance. The GRA further confirms a stronger correlation between adsorption time and adsorption capacity, highlighting the greater influence of adsorption time on adsorption performance compared to specific surface area. It indicates that the regulation of operational parameters is more practically significant in certain situations compared to the structural characteristics of the material itself. Table 5 presents the results of hierarchical correlation analysis based on these weight calculations. It indicates that rapeseed sprout biochar is most effective for Cu removal, banana peel biochar excels in Pb removal, and nutshell biochar is optimal for Cr removal. By combining AHP and GRA, this study not only clarifies the key factors affecting the adsorption behavior of biochar and their weights but also provides a theoretical basis and practical guidance for the optimal application of different biochars in the treatment of specific heavy metal pollution.

Table 4. Grey correlation.

Evaluation unit	Relatedness	Rankings
Adsorption time (h)	0.783	1
Specific surface area (m^2/g)	0.766	2

Table 5. Weight calculation results of the biochar raw material.

Pollutants in wastewater	Biochar raw material	Calculated value (mg/g)
Cu	Poultry bedding	45.30
	Alfalfa sprouts	28.22
	Viola odorata buds	32.97
	Canola sprout	66.94
	Wheat straw	32.66
	Treacle	62.66
	Potato peel biochar	66.07
Pb	Cauliflower leaf	117.26
	Banana skin	234.79
	Grapefruit peel	63.69
	Jujube	83.80
	Corn cobs and coffee Husks	26.51
	Sludge biochar	43.70
Cr	KOHBC	216.10
	Jujube charcoal	160.25
	Zn biochar	74.67
	Nutshell biochar	378.87
	Rice husk biochar	84.17

Conclusions

In this study, the performance of various biochars in adsorbing pollutants was thoroughly evaluated and compared using a combination of AHP and GRA. Based on the AHP analysis, adsorption capacity holds the highest weight at 64.83%, followed by adsorption time at 22.97%, and specific surface area at 12.20%. This study identifies adsorption capacity as pivotal in decision-making, affirming its status as the most critical indicator. Additionally, adsorption time exhibits a slightly lesser impact on adsorption performance compared to adsorption capacity, while specific surface area shows comparatively lower influence. GRA further underscores the strong relationship between adsorption time and capacity, whereas the correlation between specific surface area and capacity is modest. This research identifies optimal biochar selections for removing different pollutants: rapeseed sprout biochar is optimal for Cu removal, banana peel biochar for Pb removal, and fruit shell biochar for Cr removal. Compared to previous studies that solely utilized the AHP or GRA methods, this study offers a more comprehensive and in-depth evaluation perspective through their combined application. Furthermore, this study not only focuses on the adsorption performance of biochar materials but also delves into the key factors influencing this performance and their interrelationships. These findings offer crucial guidance for applying biochar in environmental management, enhancing pollutant removal processes, optimizing material choices, and supporting environmental protection and sustainable development initiatives. The findings of this study can be directly applied to environmental engineering fields such as wastewater treatment and soil remediation. By selecting suitable biochar materials, the removal efficiency of pollutants can be significantly enhanced, and the cost of treatment can be reduced. Future research can further explore the impact of different preparation conditions on the performance of biochar, as well as the composite application of biochar with other environmental materials, providing more innovative solutions for environmental protection.

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Artificial Intelligence Usage Disclosure

During the writing of this paper, a large language model based on artificial intelligence was used to refine the language and optimise the expression. All experimental design, raw data collection, data analysis and research conclusions were carried out independently by the author, who assumes full responsibility for the entire content of this paper.

Conflict of Interest

The authors declare no conflict of interest.

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