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Original Research

The Evaluation of Heavy-Metals Pollution in Soil Based on a Comprehensive Connection Cloud Model

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Abstract

Evaluation of heavy metal pollution in soil mass relies mainly on index methods. Choosing suitable methods to process indexes is key to obtaining accurate and reasonable evaluation results. Connection cloud models have been commonly used to evaluate pollution indexes. However, generating a cloud at each grade for each index is a tedious calculation. To address the randomness and fuzziness of soil heavy metal pollution evaluation indicators, we propose a comprehensive connection cloud model that couples the connection clouds of all indicators at each grade as sub-clouds. We establish the model by combining the weights of each indicator to determine the soil heavy metal pollution grade. The proposed model is effective and feasible for the evaluation of soil heavy metal pollution, as demonstrated through examples and comparisons with other methods. The comprehensive connection cloud model overcomes the traditional cloud models' defect of requiring normal distribution for evaluated indicators and considers the interaction between indicators. Thus, it provides a novel route for uncertainty analysis, considering the fuzzy randomness between multiple interrelated indicators.

Keywords: heavy metals, soil pollution evaluation, connection cloud, comprehensive connection cloud

Introduction

Soil mass is an irreplaceable natural resource for human beings and a vital component of the ecosystem. With the rapid development of industrialization, excessive heavy metal elements in the soil can degrade soil quality and deteriorate the ecological environment [1]. This problem is becoming increasingly serious [2]. Heavy metals in soil cannot be degraded and tend to accumulate, which affects crop yield and quality, and harms human health through the food chain. Therefore, it is crucial to analyze heavy metal pollution in soil based on local conditions and take appropriate measures to control soil pollution. Reasonable evaluation of heavy metals pollution in soil is particularly meaningful in providing a scientific basis for the prevention and management of soil pollution.

Currently, the methods for evaluating heavy metal pollution in soil mass mainly rely on index methods [3]. These methods involve substituting pollutant concentration values into mathematical formulas to obtain an index that is compared to corresponding

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evaluation standards to determine the level of pollution. The index methods include the single factor index method [4, 5], Nemerow comprehensive index method [4, 6], pollution index method [7, 8], geo-accumulation index method [9, 10], enrichment factors method [11] and potential ecological hazard index method [12, 13]. Although these evaluation methods are simple and easy to operate, they ignore the complexity and fuzziness of soil heavy metal pollution.

To overcome these shortcomings, various mathematical theories such as the fuzzy mathematic method [4, 14-16], analytic hierarchy process [17, 18], grey theory method [19], and extension method [20] have been presented to specify the pollution grade of samples based on measured values of some pollution indicators. These methods have made some achievements in evaluating soil heavy metal pollution, but they have some limitations in their processes. For instance, the fuzzy evaluation method overemphasizes the function of extreme values in the calculation process, making the evaluation result controlled by individual factors; the analytic hierarchy process has a lower utilization rate for actual measured values, reducing the accuracy of evaluation; the grey theory method tends to perform lower accuracy when it deals with scattered data; the extension theory often ignores the boundary fuzziness of the object to be evaluated. These deficiencies can cause the evaluation results to be inconsistent with the actual situation.

Furthermore, it is important to note that current evaluation methods often overlook the multiple uncertainties of evaluation indicators, which can have significant impacts on the accuracy of the results. These uncertainties include randomness and other factors that cannot be ignored. In order to address this issue, Liu et al. [21] developed a one-dimensional cloud model [22] based on the connection numbers theory to analyze soil heavy metal pollution. When compared with the models mentioned earlier, the connection cloud model can better consider the transformation trend of a rating between different grades to simulate the distribution of the indicator in a finite interval. However, the one-dimensional connection cloud ignores the interaction among indicators, and its calculation process may become complex for multiple objective problems with a larger number of samples. The multi-dimensional connection can avoid this shortcoming well. Liu et al. [23] used a multi-dimensional connection cloud to evaluate soil mass pollution in Wanjiang, addressing the issues that the distribution state of the evaluation indicators should be in finite intervals and that complicated calculations are required for multi-factor problems. Although the multi-dimensional connection cloud takes into account the different influences of various indicators on the evaluation results, it may be misjudged when the value of one certain indicator is too large or zero. Additionally, toxicity and concentration are both factors which affect the pollutant evaluation, however, nearly all existing cloud models do have not corresponding mechanisms to handle the differences brought by the two factors and coupling effects, while weighting operation can solve this issue to some extent. Thus, to overcome the defects of existing cloud models and consider the effects of multiple uncertainties of indicators, a comprehensive connection cloud model is discussed here to evaluate heavy metals pollution in soil.

The aim of this paper is to present a comprehensive cloud model for the evaluation of heavy metals pollution in soil. In the evaluation process, the novel model takes into more comprehensive consideration the interrelation of various evaluation indicators. Assembled connection degree is proposed to depict the degree of heavy metals pollution in soil from a new perspective and its quantitative transformation between various grades. The feasibility of the proposed method is confirmed and compared with other methods in a case study.

Materials and Methods

Li et al. [24] proposed a cloud model that can convert qualitative concepts into quantitative data, but it assumes that indicators follow a normal distribution in infinite intervals. In practical engineering, the indicators may not conform to the normal distribution, which may not always hold in practical engineering scenarios. To address this limitation, Wang [22] incorporated connection number theory into the cloud model and developed an improved version called the connection cloud model. The definition and workflow of the connection cloud model are presented below:

Connection Cloud Model

For the research object being evaluated by the connection cloud model, the levels should be divided into *m* categories (*j = 1, 2, ..., m*) and the evaluation system should correspond to *n* indicators (*i = 1, 2, ..., n*). Assuming that a certain indicator or a single indicator *i* is located in the level *j* interval (x_{ij}), it is composed of two clouds on the left and right with the expected value Ex_j as the dividing point. The cloud drops are based on the numerical characteristics (*Ex, En, He, a, k*) and the number of drops *N*.

The connection degree $\mu \in [0,1]$, indicates the possibility that the indicator belongs to a certain grade. For a cloud drop x_j, the connection degree is calculated as follows:

$$\mu_j = exp\left(-4.5\left|\frac{x_j - Ex_j}{3En_j'}\right|^{k_j}\right) \tag{1}$$

The expected value can be presented as:

$$Ex_{ij} = \frac{C}{ijmax^2_{+ijmin}} \tag{2}$$

The entropy is:

$$En_{ij} = \frac{a_{ij}}{3} \tag{3}$$

The hypertrophy is:

$$He_{ij} = \beta \tag{4}$$

All above three characteristics can be integrated as:

$$k_{ij} = \frac{ln\left(\frac{ln\,4}{9}\right)}{ln\left(\frac{C_{ij}-Ex_{ij}}{3En_{ij}}\right)} \tag{5}$$

where C_{ijmax} and C_{ijmin} are the thresholds of the interval-valued grade j of the indicator i. α_{ij} represents the -half-interval length. β is a constant. C_{ij} represents the lower limit of a discussed classification rating C_{ijmin} or the upper limitation C_{ijmax}. k_{ij} is the distribution density function of x_{ij}.

A Comprehensive Connection Cloud Model

The original connection cloud models are constructed by computing the mathematic characteristics of the same or different types of evaluation indicators [25]. In contrast, the comprehensive connection cloud model computes the mathematical characteristics of the connection cloud using different indicators to obtain new characteristics, and integrates the grade clouds of each indicator into a comprehensive cloud to achieve the evaluation task. This process is illustrated in Fig. 1.

In the comprehensive connection cloud, the grade cloud of the evaluation indicator is composed of left and right asymmetric connection clouds with *Ex* as the dividing point. The connection degree is represented by numerical characteristics (*Ex, En, He, k*) and the number of cloud drops *N*, which is still calculated by Equation (1).

For level *j*, the parameters counterpart to the original connection cloud mode are modified or integrated by the objective weights:

$$Ex_j = \sum_{i=1}^{m} W_i Ex_{ij} \tag{6}$$

$$En_j = \sqrt{\sum_{i=1}^{m} W_i En_{ij}^2} \tag{7}$$

$$He_j = \sqrt{\sum_{i=1}^{m} W_i He_{ij}^2} \tag{8}$$

$$k_j = \frac{ln\left(\frac{ln\,4}{9}\right)}{ln\left(\frac{\sum_{i=1}^{m} W_i C_{ij} - Ex_j}{3En_j}\right)} \tag{9}$$

According to set pair theory, in the process of connection cloud simulation, the connection degree belonging to [0, $e^{-4.5}$] is defined as the contrary, [$e^{-4.5}$, 0.5] is defined as the discrepancy, [0.5, 1] is defined as the identity. *x* is cloud drop satisfying normal distribution $N(Ex,En'^2)$, *En*' is a random number suiting the normal distribution $N(En,He^2)$. *Ex, En, He,* and *k*

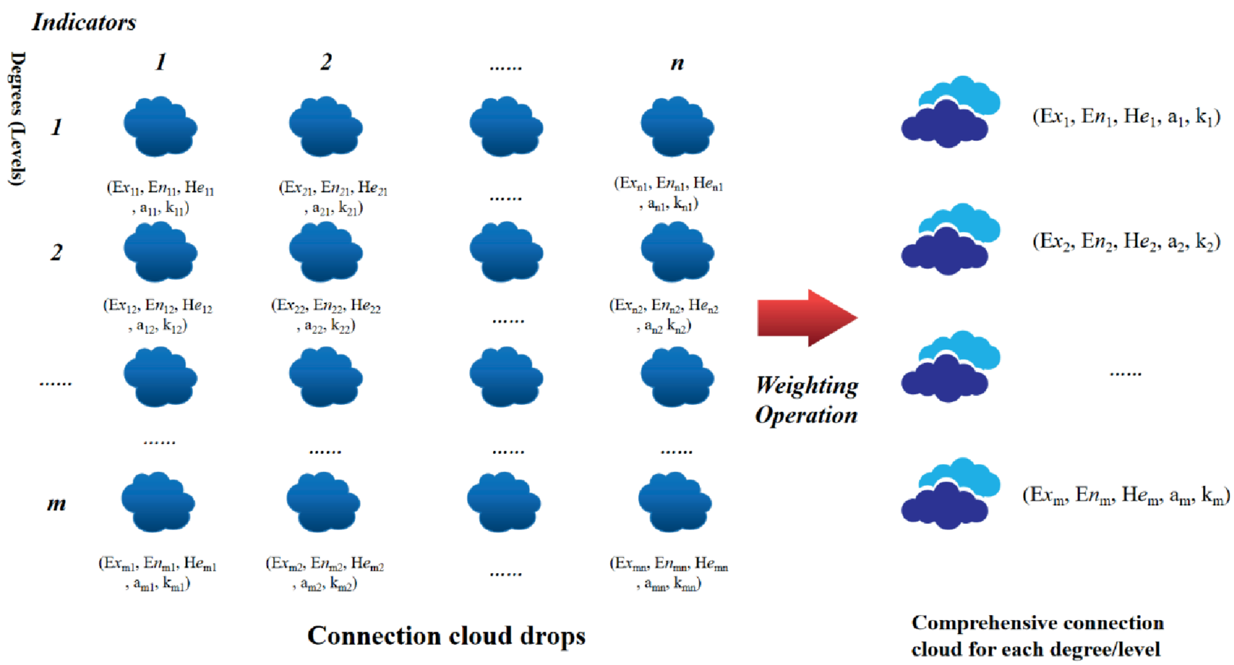

Fig. 1. Conceptional description of the comprehensive connection cloud model.

are the numerical characteristics, which represent the expected value, entropy, hyper entropy, and the order of distribution function, respectively.

Evaluation Approach Based on Comprehensive Connection Cloud Model

Basic Principle

The fundamental evaluation principle of the comprehensive connection cloud model can be described as follows: Initially, the length of the left and right half intervals of each grade is determined based on the normalized evaluation standard. Next, the numerical characteristics (*Ex, En, He, k*) are determined separately for each grade of the evaluation indicators. Lastly, the comprehensive clouds are generated based on the connection cloud of each evaluation indicator. The pollution grade of the soil is evaluated according to the degree of certainty that the sample indicators belong to each grade.

Evaluation Procedure

The basic process of soil heavy metal pollution evaluation based on a comprehensive connection cloud model is shown in Fig. 2.

Based on the flow, the detailed evaluation procedure is consisting of 6 steps as follows.

Step 1: According to the actual situation of heavy metal pollution of soil in target regions, select appropriate evaluation indicators and classification standards, assuming that there are m evaluated indicators ($i = 1, 2, \ldots, m$) and n pollution grades ($j = 1, 2, \ldots, n$).

Step 2: To unify the dimensions of different heavy metal indicators, the evaluation criteria, and sample values can be normalized. The normalization formula is shown in Eq. (10)

$$s_{ij} = \frac{x_{ij} - x_{min(j)}}{x_{max(j)} - x_{min(j)}} \tag{10}$$

Where s_{ij} is the normalized value of x_{ij}, $x_{\max(j)}$ and $x_{\min(j)}$ are the maximum and minimum concentration values of the jth heavy metal indicator.

Step 3: Choose or calculate appropriate weights for heavy metals to evaluate soil heavy metal pollution, considering the concentration and the toxicity grade of heavy metals. Dou et al. [14] used exceeding standard weighting to calculate the weights for each heavy metal which combine heavy metal concentration with toxicity grade are expressed as:

$$\omega_i = \frac{\frac{x_i}{\sum_{j=1}^{n} s_{ij}}}{\sum_{i=1}^{m} \frac{x_i}{\sum_{j=1}^{n} s_{ij}}} \tag{11}$$

$$W_i = \frac{\frac{\omega_i}{t_i}}{\sum_{i=1}^{m} \frac{\omega_i}{t_i}} \tag{12}$$

$$\begin{cases} a_{ij(L)} = Ex_{ij} - C_{i(j-1)min} \\ a_{ij(R)} = C_{i(j+1)max}^{ij} - Ex_{ij} \end{cases} \tag{13}$$

Where x_i is the measured value, t_i is the toxicity grade of the pollution factor, ω_i is the concentration weight of each pollution factor, and W_i is the weight synthesized concentration and toxicity grade.

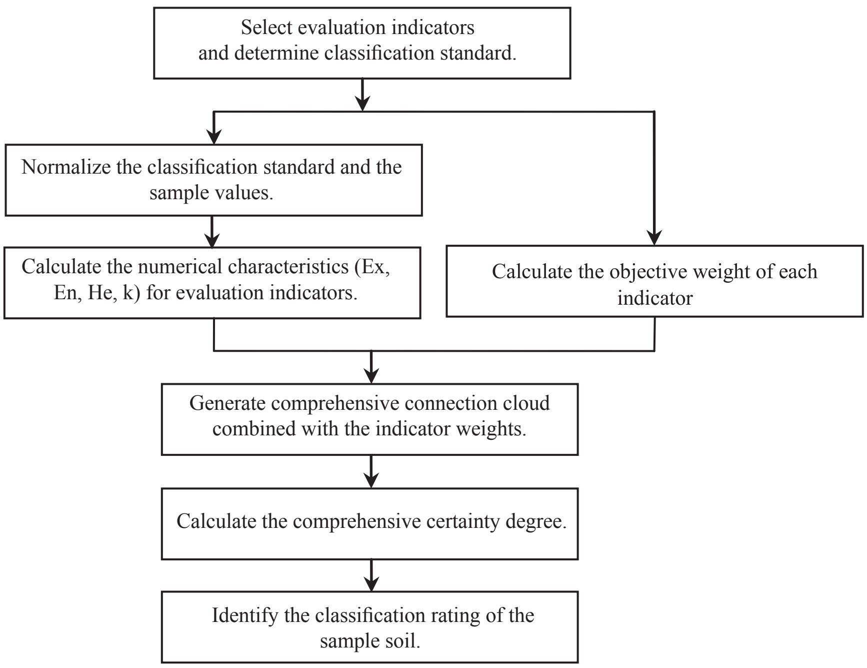

Fig. 2. Flow chart of soil heavy metal pollution evaluation based on comprehensive connection cloud model.

Step 4: The numerical characteristic parameters (Ex_{ij}, En_{ij}, Ee_{ij}, k_{ij}) of the connection cloud can be calculated by Eq.(5) to (9) [26]. Then, the connection cloud of each grade for indicators can be generated.

Step 5: According to the numerical characteristics of the connection cloud of each indicator, combined with the weights to determine the comprehensive cloud numerical characteristics, which can be achieved by Eq. (10) to Eq. (13). The equations can be demonstrated by the mathematical induction [27]. Then, the comprehensive connection degree is specified by Eq. (1).

Step 6: Determine the grade of soil heavy metal pollution for the sample according to the maximum membership rule.

Case Study

Data

To verify the feasibility and reliability of the proposed model, 18 samples [14, 19] were analyzed and compared. The concentrations of Cd, Hg, Pb, Cr, Cu, and Zn were selected as the evaluation indicators, and the soil heavy metal pollution was classified into five grades: cleaning (I), poor cleaning (II), light pollution (III), moderate pollution (IV), and severe pollution (V). The classification standard and measured indicator values of samples are shown in Tables 1 and 2, respectively.

Table 1. Classification standard for soil heavy metal pollution [14].

Ranks	Cleaning (I)	Poor cleaning (II)	Light pollution (III)	Moderate pollution (IV)	Severe pollution (V)	Toxicity index
Cd	0.1204	0.2523	0.6	1.4	2	2
Hg	0.092	0.2592	0.45	1.05	1.5	1
Pb	23.35	36.09	150	350	500	3
Cr	74.88	99.54	150	350	500	5
Cu	28.37	40.63	120	280	400	4
Zn	83.68	116.75	240	560	800	6

Table 2. Measured values of the samples (mg/kg) [19].

Sample	Cd	Hg	Pb	Cr	Cu	Zn
P1	0.4620	0.178	22.870	75.720	26.350	119.950
P2	0.3040	0.225	24.620	75.710	28.760	118.530
P3	0.2200	0.230	24.200	61.000	28.900	86.600
P4	0.1000	0.160	14.770	73.590	22.890	76.960
P5	0.8700	0.300	37.150	92.590	50.660	148.280
P6	0.4840	0.190	20.730	88.110	44.260	98.630
P7	8.2000	0.600	50.000	-	40.600	838.460
P 8	-	0.030	26.360	71.620	22.780	76.810
P 9	0.1200	0.110	21.450	68.170	28.240	82.550
P10	0.1200	0.060	16.900	59.800	21.800	70.000
P11	0.1090	0.131	34.000	66.000	230.400	79.800
P12	0.1064	0.158	32.300	68.800	200.000	83.200
P13	0.1262	0.144	33.100	66.400	225.900	79.800
P14	0.0905	0.151	30.900	67.900	200.500	82.700
P15	0.4331	0.204	40.300	97.000	45.900	221.500
P16	0.5267	0.677	38.900	94.700	46.200	159.400
P17	0.4218	0.536	37.200	101.000	46.000	138.700
P18	0.3458	0.310	37.300	94.200	72.400	130.600

Table 3. Weights of heavy metals in the samples.

Sample	Cd	Hg	Pb	Cr	Cu	Zn
P1	0.3694	0.3717	0.0378	0.0902	0.053	0.0777
P2	0.2485	0.4801	0.0415	0.0922	0.0592	0.0785
P3	0.1993	0.5438	0.0452	0.0823	0.0659	0.0635
P4	0.1286	0.5371	0.0392	0.1410	0.0741	0.0801
P5	0.4113	0.3701	0.0362	0.0652	0.0603	0.0568
P6	0.3598	0.3686	0.0318	0.0976	0.0828	0.0594
P7	0.7699	0.1470	0.0097	0.0000	0.0096	0.0637
P 8	0.0000	0.2181	0.1516	0.2972	0.1597	0.1733
P 9	0.1737	0.4156	0.0641	0.1470	0.1029	0.0968
P10	0.2344	0.3058	0.0681	0.1739	0.1071	0.1107
P11	0.0863	0.2705	0.0555	0.0778	0.4587	0.0511
P12	0.0846	0.3277	0.0530	0.0814	0.3999	0.0535
P13	0.0969	0.2886	0.0525	0.0759	0.4365	0.0496
P14	0.0741	0.3228	0.0522	0.0828	0.4132	0.0548
P15	0.2911	0.3578	0.0559	0.0971	0.0776	0.1205
P16	0.1908	0.6401	0.0291	0.0511	0.0421	0.0468
P17	0.1853	0.6146	0.0337	0.0661	0.0509	0.0493
P18	0.2083	0.4874	0.0464	0.0845	0.1097	0.0637

Table 4. The numerical characteristics values (Ex, En_L, En_R, He, k_L, k_R) of sample 1.

Evaluation Indicator	Cleaning (I)	Poor cleaning (II)	Light pollution (III)	Moderate pollution (IV)	Severe pollution (V)
Cd	(0.030,0.000,0.090, 0.010,0.000,0.853)	(0.093,0.031,0.069,0. 010,1.801,1.019)	(0.213,0.051,0.162, 0.010,3.313,1.086)	(0.500,0.125,0.167, 0.010,2.990,2.041)	(0.850,0.183,0.000,0. 010,1.440,0.000)
Hg	(0.031,0.000,0.090, 0.010,0.000,0.861)	(0.117,0.039,0.061,0. 010,2.520,1.574)	(0.236,0.058,0.155, 0.010,1.847,0.942)	(0.500,0.109,0.167, 0.010,3.800,2.041)	(0.850,0.183,0.000,0. 010,1.440,0.000)
Pb	(0.023,0.000,0.092, 0.010,0.000,0.757)	(0.059,0.020,0.080,0. 010,1.214,0.637)	(0.186,0.046,0.171, 0.010,9.266,1.242)	(0.500,0.143,0.167, 0.010,2.460,2.041)	(0.850,0.183,0.000,0. 010,1.440,0.000)
Cr	(0.075,0.000,0.075, 0.010,0.000,1.700)	(0.174,0.058,0.042,0. 010,0.956,1.149)	(0.250,0.033,0.150, 0.010,2.744,0.854)	(0.500,0.100,0.167, 0.010,4.579,2.041)	(0.850,0.183,0.000,0. 010,1.440,0.000)
Cu	(0.035,0.000,0.088, 0.010,0.000,0.931)	(0.086,0.029,0.071,0. 010,1.083,0.710)	(0.201,0.043,0.166, 0.010,6.948,1.158)	(0.500,0.133,0.167, 0.010,2.714,2.041)	(0.850,0.183,0.000,0. 010,1.440,0.000)
Zn	(0.052,0.000,0.087, 0.010,0.000,1.166)	(0.125,0.042,0.062, 0.010,1.038, 0.849)	(0.229,0.042,0.157, 0.010,4.641,1.080)	(0.500,0.120,0.165, 0.010,3.015,2.000)	(0.538,0.179,0.000,0. 010,1.466,0.000)
Synthesization	(0.036,0.000,0.088, 0.010,0.000,0.938)	(0.110,0.038,0.064, 0.010,1.716, 1.154)	(0.225,0.051,0.159, 0.010,2.662,2.153)	(0.500,0.118,0.166, 0.010,3.268,2.038)	(0.850,0.183,0.000,0. 010,1.442,0.000)

Model Validation

Based on the above calculation models mentioned above, numerical characteristics values (Ex, En_L, En_R, He, k_L, k_R) of the connection cloud were calculated for each grade using Eq. (2) and Eqs (4) to (9); Then, Eq. (3) was used to calculate the weights of evaluation indicators, the results are shown in Table 3; Combined with the weights, numerical characteristics values of the connection cloud were obtained using Eqs (10) to (13). For instance, taking the data of sample P1, numerical characteristics values of each grade for each evaluation

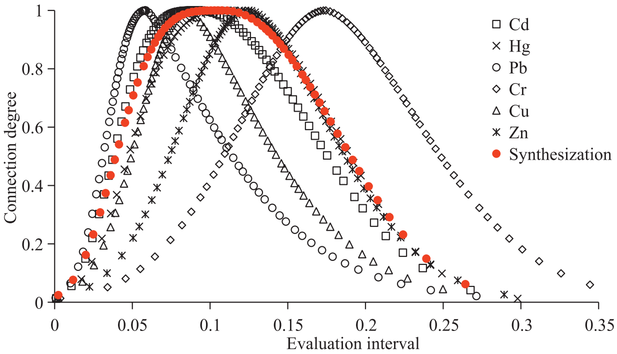

Fig.3. Clouds of each indicator and comprehensive cloud in Grade 2.

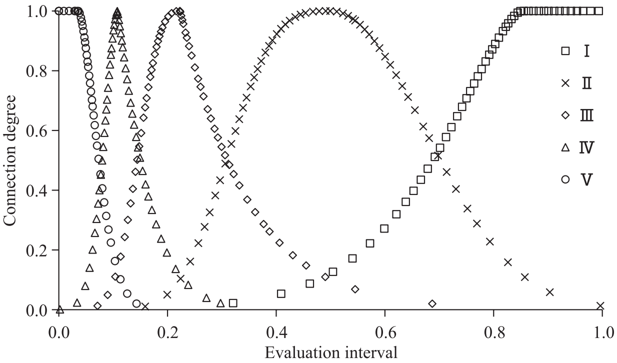

Fig.4. Comprehensive connection clouds of each grade.

indicator were shown in Table 4. Using the numerical characteristics, the connection clouds corresponding to every indicator for each grade were obtained, and a new cloud was formed by synthesizing all indicators. Taking grade II as the example, the clouds of each indicator and the comprehensive cloud are illustrated in Fig. 2. In the same manner, the comprehensive clouds of grade I to V were obtained, respectively, as shown in Fig. 3. The connection degree of each grade for samples listed in Tables 5 and 6 was obtained by Eq (1).

Results and Discussion

The evaluation results obtained from the proposed model were compared with other methods and are listed in Tables 5 and 6. As shown in Table 5, the evaluation results from the proposed model are almost consistent with those from the improved fuzzy mathematical method, connection numbers, and the D-S theory method. However, the evaluation results of samples P1, P4, and P6 using the proposed model were one level higher than the other two methods. For sample P1, the heavy metal element Cd and Zn were located in grade III, Hg and Cr were located in grade II, and Pb and Cu were located in grade I. But the toxicity index of Hg and Cd ranked first and second, respectively, and the weights of both were much bigger than others. Therefore, it is more reasonable to rate sample P1 as grade III. While connection numbers and the D-S theory method fused indicators several times ignoring differences in toxicity index, which may caused by the characteristics of D-S theory that it is susceptible to interference from multiple conflicting indicators [28]. The same reasoning applied to samples P4 and P6.

In Table 6, we can observe significant differences among the three methods: the evaluation results of P11 to P14 and P16 calculated by the proposed model differ from those of the Nemerow pollution index method. Specifically, the proposed method assigns grade III and IV, but they are grades IV or V based on the Nemerow composite index method. In fact, for each of the five samples, only one indicator is in grade IV, and the other indicators are in a lower grade. The Nemerow index method places too much emphasis on the impact of the pollutants with the highest pollution index on the environmental quality [29, 30]. In some cases, the results

Table 5. The results of the sample (P1-10).

Sample	μ_{I}	μ_{II}	μ_{III}	μ_{IV}	μ_{V}	Proposed model	Connection numbers and D-S theory method	Improved fuzzy mathematical method
P1	0.110	0.389	0.644	0.048	0.011	III	II	II
P2	0.151	0.630	0.370	0.016	0.011	II	II	II
P3	0.182	0.806	0.259	0.012	0.011	II	II	II
P4	0.351	0.808	0.057	0.012	0.011	II	I	I
P5	0.034	0.414	0.944	0.422	0.021	III	III	III
P6	0.096	0.317	0.746	0.054	0.011	III	II	II
P7	0.012	0.322	0.064	0.032	0.768	V	V	V
P8	0.601	0.322	0.017	0.013	0.011	I	I	I
P9	0.478	0.539	0.020	0.012	0.011	II	II	I
P10	0.662	0.288	0.014	0.012	0.011	I	I	I

Table 6. The results of the sample (P11-18).

Sample	μ_I	μ_{II}	μ_{III}	μ_{IV}	μ_V	Proposed model	Nemerow pollution index method	Improved grey clustering method
P11	0.074	0.073	0.857	0.740	0.046	III	V	IV
P12	0.082	0.113	0.974	0.470	0.028	III	V	IV
P13	0.076	0.088	0.895	0.675	0.041	III	V	IV
P14	0.081	0.100	0.968	0.499	0.029	III	IV	IV
P15	0.086	0.256	0.837	0.055	0.011	III	III	III
P16	0.018	0.239	0.741	0.838	0.033	IV	V	IV
P17	0.023	0.203	0.951	0.431	0.017	III	III	III
P18	0.071	0.228	0.872	0.046	0.011	III	III	III

of the Nemerow pollution index can hardly distinguish the difference in soil environmental quality pollution. The same reason also causes differences between the improved grey clustering method and the proposed model, while the grey clustering method relatively dilutes the impact of a single indicator [31] and results are closer to those obtained from the proposed model.

In Table 7, the results obtained from the proposed model are highly consistent with those obtained from the fuzzy mathematical method, except for P1, 5, 6 and 9. For P6, the grades of six pollutant indicators are III, II, I, II, III, and II , with the most toxic heavy metal Hg located in grade II, while the heavy metals Cd and Pb are located in grade III. Both the fuzzy mathematical and extension methods assume that the grade is II because they mainly rely on a single indicator as a reference or tend to be affected by the most notable factors [32]. However, the proposed comprehensive connection cloud model considers multiple indicators in a more integrated way, leading to more accurate results.

It is also meaningful to compare the proposed connection cloud with the original connection cloud model. As for calculated results, results calculated by the comprehensive connection cloud are relatively more conservative than those calculated by one-dimensional connection cloud model: for P4, its calculated grade is higher than the latter one grade, because of the weighting strategy, it tends to rely on the dominant indicator when most indicators tend to be the same grade, which is a significant advantage when it is used for weakly coupled data analysis [33].

What is more, as Table 8 shows, the proposed comprehensive connection cloud model tends to output compromise results compared to the highly inconsistent phenomenon between some different evaluation methods. However, it may be caused by the instabilities of corresponding evaluation methods in certain scenarios, which is a common problem with nearly all methods [34].

These findings demonstrate the feasibility and reliability of evaluating soil heavy metal pollution using the proposed model, which also has several advantages summarized as follows:

(1) The weights of the evaluation indicators not only consider the concentration of pollutants but also the toxicity of pollutants, which is more reasonable

Table 7. Comparison with other methods for samples 1-10.

Sample	Fuzzy mathematical method	Extension method	One dimensional connection cloud model	Proposed model
P1	I	II	II	II
P2	II	II	II	II
P3	II	II	II	II
P4	II	I	I	II
P5	II	III	III	III
P6	II	II	II	III
P7	V	II	V	V
P8	I	I	I	I
P9	I	II	II	II
P10	I	I	I	I

Table 8. Comparison with other methods for samples 11-18.

Sample	Nemero composite index method	Potential ecological risk index method	Proposed model
P11	V	II	III
P12	V	II	III
P13	V	II	III
P14	IV	II	III
P15	III	II	III
P16	V	IV	IV
P17	III	III	III
P18	III	II	III

than existing models. The simulation process for cloud drops takes into account the weights of indicators, comprehensively reflecting the synergistic effect of various heavy metals in soil, leading to more objective evaluation results than other methods.

(2) The comprehensive connection cloud couples the indicators into a cloud, exploring the certainty and uncertainty of the transition situation of the indicators between different grades from an overall perspective, to simulate the actual distribution of a fuzzy random indicator. Meanwhile, the calculation process of the comprehensive connection cloud is greatly simplified. From Fig. 2 and Fig. 3, it can be concluded that 6 clouds need to be generated for each grade of one-dimensional connection cloud, and a total of 30 clouds need to be generated for each sample. However, the comprehensive connection cloud only needs to conduct one calculation for each grade after the indicators are coupled so that the computing speed can be improved.

Conclusions

Evaluation of soil heavy metal pollution is of great significance to the human ecological environment . However, existing evaluation methods have certain shortcomings, as they tend to be affected by a variety of uncertain indicators, which are mostly distributed in limited intervals. Therefore, this paper proposes the comprehensive connection cloud model for the evaluation of soil heavy metal pollution, and the following conclusions are drawn:

(1) The proposed comprehensive connection cloud model comprehensively considers the uncertainty and correlation between different indicators to evaluate soil heavy metal pollution. This model was verified by 18 examples and compared with other methods, which shows that the evaluation results of the model are reliable.

(2) The comprehensive connection cloud model integrates multiple indicators and considers their influence on the evaluation results to avoid the disadvantage that one indicator has too much influence on the evaluation results. The proposed model overcomes the shortcoming that the normal cloud requires the indicators to obey the normal distribution, making it better at simulating the actual distribution state of each indicator and describing the transformation trend between different grades.

(3) The comprehensive connection cloud uses the connection clouds of all indicators in each grade as sub-clouds to generate a comprehensive cloud. When the characteristic values of the comprehensive connection cloud are calculated, the weights are coupled into the calculation model, which avoids the deficiency of the multi-dimensional connection cloud. Compared with the one-dimensional connection cloud, the comprehensive connection cloud owns higher computational efficiency; and compared with the normal connection cloud, the comprehensive connection cloud does not require indicator data to suit the normal distribution, and also avoids the singularity phenomenon in the multi-dimensional connection cloud; in addition, the comprehensive connection cloud effectively coordinates the differences in indicator weights caused by the importance of different factors through weighting operations, to correct evaluation results.

(4) To get more accurate evaluation results, GIS technology can be used to collect raw data on soil heavy metal pollution [35], which can generate mesh heatmaps to show the spatial distribution of soil heavy metal pollution and a variety of evaluation methods can be used simultaneously.

Overall, the proposed comprehensive connection cloud model provides a new perspective for the evaluation of soil heavy metal pollution and can be applied in practical evaluation work.

Conflict of Interest

The authors declare no conflict of interest.

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