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Evaluation of coarse aggregate quality grade of recycled concrete based on the principal component analysis-cloud model

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The quality grade assessment of coarse aggregate in recycled concrete has great significance for engineering quality, so the accurate estimation of its quality grade is vital. However, many factors affect its quality level, and its assessment procedure has a certain fuzziness and randomness. To overcome the abovementioned problems, the principal component analysis-cloud model was introduced. It is a combination of the principal component analytical method (PCA) and the normal cloud model and has the advantages of the two methods, as well as being widely applied to assess the quality level of different construction materials. To evaluate the coarse aggregate quality grade of recycled concrete in the present paper, the principal component analytical method (PCA) was applied to reduce the dimension of data and calculate the weight of each index, then a model of coarse aggregate quality based on cloud theory was constructed. According to the characteristic parameters of the cloud model, the coarse aggregate quality grade was determined. The conclusions indicate that the method is feasible for the accurate assessment of quality grade assessment of coarse aggregate, and its accuracy is very high. So, a new approach can be provided for the quality grade assessment of coarse aggregate in the future.

KEYWORDS

cloud model, recycled concrete, quality grade, evaluation, coarse aggregate

1 Introduction

The quality grade evaluation of recycled concrete is of great significance in engineering construction. It can provide a powerful reference for construction units to achieve a rational use of recycled coarse aggregate and to comprehensively and accurately reflect the physical and mechanical properties of recycled concrete aggregate (Gu et al., 2021).

Because recycled concrete aggregate is defined as the recycling and application of the waste concrete block, it not only saves many construction costs but can also play a good role in energy conservation and environmental protection (Gu et al., 2021). As such, recycled concrete aggregates have gained increasingly more attention in many developed countries, which have carried out an abundance of experimental research (Gu et al., 2022), especially in determining the quality grade of recycled concrete aggregates. At present, there is a "Quality trial regulation of recycled concrete", which was published in Japan in 1994, that selects water absorption and crushing index as the main measurement parameters to evaluate the quality grade of aggregates. However, the British Standards (1992) and the ASTM standards (USA) (2003), as well as other foreign scholars in this area of evaluation research, take the minimum apparent density, the maximum water absorption, the maximum content of needle-like particles, the maximum impact value, the maximum content of chlorine, and the maximum content of sulfate as the criteria for judging the quality grade of recycled coarse aggregate (Gu et al., 2021). Of course, domestic research on quality grade evaluation of recycled concrete coarse aggregate has never been interrupted. Based on a large number of experimental studies, the Ministry of Construction in China promulgated the standard of recycled aggregate for concrete in 2010 (GB/T 25,177-2010). It was put forward that the recycled coarse aggregate of concrete can be divided into three grades by 10 indexes, such as particle gradation, micro-powder content, mud content, water absorption rate, and needle-like particle content (Gu and Wu, 2016). Based on the uncertainty of the influence degree of each evaluation parameter on the quality grade of recycled concrete coarse aggregate, a fuzzy comprehensive evaluation method was put forward (Li and Wu, 2019). According to the knowledge of gray clustering evaluation theory, Bao and Wang. (2014) proposed a gray clustering evaluation model to evaluate the quality grade of recycled concrete coarse aggregates. Chai and Liu (2018) performed the quality grade evaluation of recycled concrete coarse aggregates based on the entropy weight extension theory.

The abovementioned research and evaluation methods play an essential role in guiding the rational selection of coarse aggregate in the concrete construction process (Gu et al., 2019; Gu et al., 2019). However, the methods mentioned above are limited in their ability due to the complexity and variability of influential factors that affect the coarse aggregate quality of concrete, for example, some factors are certain, some are uncertain, and some are random variables. Therefore, a comprehensive evaluation method that can better solve this kind of uncertainty and the multi-attribute problem should be sought.

The principal component analysis cloud was used in the present study to solve the problems mentioned above. For the method, the inner relationship between fuzziness and randomness was described, and the conversion between qualitative concepts and quantitative features was considered (Zhou et al., 2008; Zhou et al., 2021). Compared to the abovementioned methods, its assessment process has higher reliability and efficiency, so the suggested model has enormous application prospects.

The present research paper has been organized as follows: in Section 1, the methodology is introduced; in Section 2, a new quality assessment model of coarse aggregate is established based on the principal component analysis-cloud model; in Section 3, the results are analyzed and discussed; and in Section 4, conclusions are drawn.

2 Methodology

The principal component analysis-cloud model is a combination of the principal component analytical method (PCA) and the normal cloud model and possesses the advantages of the two methods. The principal component analytical method (PCA) was applied to reduce the dimension of data and calculate the weight of each index, whereas the normal cloud model was used to estimate the quality level.

2.1 The principal component analysis

The principal component analysis was provided by Pirsson (Sheng, 1991) in 1901. It is a statistical analysis method that converts many variables into a few principal components by dimensional reduction. The respective principal component is usually composed of the original variables by using the linear combination. They are independent of each other, and most of the information of the original variable is reflected. This method is mainly applied for dimensional reduction and weight calculation. The calculative model is listed as follows: it is assumed that there are n samples and m variables in one instance. Then, the original assessment index of $n \times m$ relative matrix X can be constructed as follows:

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \cdots & \cdots & \cdots \\ x_{1n} & \cdots & x_{nm} \end{bmatrix} \tag{1}$$

Where x_{nm} denotes the mth variable in the nth sample. Assuming that new variables z_1 z_2 z_3, $\ldots$, z_t $(t \leq m)$ are the synthetic index of dimensional reduction, then it can be met with:

$$\begin{cases} z_1 = l_{11}x_1 + l_{12}x_2 + \ldots + l_{1m}x_m \\ z_2 = l_{21}x_2 + l_{22}x_2 + \ldots + l_{2m}x_m \\ \ldots \\ z_m = l_{m1}x_1 + l_{m2}x_2 + \ldots + l_{mm}x_m \end{cases} \tag{2}$$

Where the defining principle of coefficients l is the square sum of coefficients in the different equations in the formula and is equal to 1, the principle components are independent of each other, and z_1 is the maximum variance of all the linear combination about the variables $x_1, x_2, \ldots, x_m$; z_2 is irrelevant of z_1 and the maximum variance of all the linear combination about the variables $x_1, x_2, \ldots, x_m$; likewise, z_i is irrelevant of $z_1, z_2, \ldots z_{i-1}$ and the maximum variance of all the linear combination about the variables $x_1, x_2, \ldots, x_m$.

Based on the relevant matrix, the weight coefficients of different indices can be obtained as follows (Alison et al., 2020):

1) the normalization of the sample matrix:

$$X_{ij} = \frac{x_{ij} - \overline{x_j}}{s_i} \left(i = 1, 2, \ldots, n;\ j = 1, 2, \ldots, m\right) \tag{3}$$

$$\overline{x_j} = \frac{\sum_{i=1}^{n} x_{ij}}{n}, s_j^2 = \frac{\sum_{i=1}^{n} \left(x_{ij} - \overline{x_j}\right)}{n-1} \tag{4}$$

Where x_{ij} represents the normalized jth index of the ith sample; $\overline{x_j}$ and s_j^2 represent the mean and variance of the jth index, respectively.

2) The calculation of the Pearson relative coefficient matrix R among the different indices, namely:

$$R = \left(r_{ij}\right)_{m \times m} (i = 1, 2, \ldots, m) \tag{5}$$

Where r_{ij} is the relative coefficient between the ith and jth indexes; r_{ij} can be depicted as:

$$r_{ij} = \frac{\sum_{k=1}^{m}\left(x_{ki} - \overline{x_i}\right)\left(x_{ki} - \overline{x_j}\right)}{\sqrt{\sum_{k=1}^{m}\left(x_{ki} - \overline{x_i}\right)^2\left(x_{ki} - \overline{x_j}\right)^2}} \tag{6}$$

3) The calculation of eigenvalues and eigenvectors of the relevant coefficient matrix R; the eigenvalue is marked as λ and the normalized unit eigenvector corresponding to the eigenvalue is marked as p.
4) Calculating the number of principal components. The cumulative contribution rate of principle components was calculated. Its eigenvalue was greater than 1. The accumulative contribution rate of 85%–95% corresponding to the former k principal component is depicted as:

$$v_s = \lambda_s \Big/ \sum_{s=1}^{m} \lambda_s \; (s = 1, 2, ..., m) \tag{7}$$

$$v_{\text{sumk}} = \sum_{s=1}^{k} \lambda_s \Big/ \sum_{s=1}^{m} \lambda_s \; (k = 1, 2, ..., m) \tag{8}$$

Where v_s is the contribution rate of variance at the sth principal component. v_{sumk} is the contribution rate of accumulative variance at the former k principal components.

5) the coefficient matrix of the principal component to meet the cumulative contribution rate of 80% can be extracted as:

$$U_k = (p_1, p_2, ..., p_k) \tag{9}$$

6) The calculation of different index weights ω:

$$\omega = \left|U_k \times v_k / v_{sumk}\right| \Big/ \sum_{i=1}^{k} \left|U_k \times v_i / v_{sumk}\right| \tag{10}$$

2.2 The normal cloud model

The cloud model was provided by Li et al. (1995) in the 1990s; it is a cognitive model applied to deal with the two-way conversion between qualitative concepts and quantitative data. According to vague mathematics and random mathematics, the theory is performed as a unified portrayal between the uncertainty of vague problems and the randomness of membership degree. It can deal with vague and random events; the cloud model has been successfully applied to wide-field (Xu et al., 2011).

The cloud model is defined as follows: x, Y, C is assumed as a common quantitative set, Y is called the domain; where $x \in Y$, C is the qualitative conception in the domain Y. For the random research object x in the domain Y, there still exists a random number with a stable tendency $u(x) \in [0, 1]$, then is called the membership degree of x corresponding to C, or it is called the definitive degree. The distribution of the definitive degree in the domain Y is called the membership cloud. If x meets with $x \sim N(Ex, En'^2)$, and $En' \sim N(En, He^2)$, and then can be expressed as:

$$u(x) = \exp\left[-\frac{(x - Ex)^2}{2En'^2}\right] \tag{11}$$

Where the distribution definitive degree in the domain Y is also called a normal cloud or Gauss cloud. For the quality grade of coarse aggregate, the Expectation Ex, Entropy En, and hyperentropy $\frac{dx^{(1)}}{dt} + ax^{(1)} = u$ are applied to represent the digital features of stable definition at certain coarse aggregates to demonstrate the uncertainty of the stable state. Ex can represent the point of certain conception in the domain of quality grade of coarse aggregates, namely, it is the center value of conception in the domain space; En is determined by the vagueness and randomness of the conception of quality grade of coarse aggregates and it reflects the accepting range of conception; $\frac{dx^{(1)}}{dt} + ax^{(1)} = u$ demonstrates the uncertainty of Entropy and its magnitude reflects the thickness of cloud drop. Expectation Ex, Entropy En, and hyperentropy $\frac{dx^{(1)}}{dt} + ax^{(1)} = u$ of different grades in the cloud model can be calculated as follows (Chen et al., 2022; Gu et al., 2022):

$$Ex = \frac{c^+ + c^-}{2} \tag{12}$$

$$En = \frac{c^+ - c^-}{6} \tag{13}$$

$$H_e = k_1 \tag{14}$$

Where c^+ and c^- are, respectively, the upper and lower bounds corresponding to the grade standard of a specific index; for the case of a single boundary, the default bound can be determined by using the upper and lower bounds of actual data at the same grade. The hyperentropy $\frac{dx^{(1)}}{dt} + ax^{(1)} = u$ can be selected as a proper constant k according to the maximum range of different indices, commonly in the cloud model, $H_e \le 0.5$. If $H_e \ge 0.5$, it demonstrates the distance of adjacent cloud drops is too great, so the discreteness of cloud drops is bad. k is set as 0.01 in the investigation.

If a variable has only a single boundary, such as $[-\infty, x_u]$ or $[x_l, +\infty]$, the corresponding characteristic parameters are depicted as follows (Zhou et al., 2016; Klauer et al., 2016):

$$E_x = 1.5x_l \tag{15}$$

$$E_n = \frac{E_x}{6} \tag{16}$$

3 The establishment of the assessment model

To assess the quality grade assessment of coarse aggregates, the assessment model should be established. The procedure is listed as follows:

3.1 The construction of an index system

Many factors result in the quality grade of coarse aggregate; according to the relevant research (Wang and Park, 2001), the quality grade of coarse aggregate is affected by seven assessment indicators: apparent density(X_1), the porosity (X_2), the sturdiness(X_3), the crushing index(X_4), the micronutrient content(X_5), the soil content(X_6), and the water absorption(X_7).

TABLE 1 The classification standard of the assessment index.

Assessment index	The stability level of seismic slopes				
	I	II	III	IV	V
X_1	>2,450	(2,350, 2,450)	(2,300, 2,350)	(2,250, 2,300)	≤2,250
X_2	<47	(47, 49)	(49, 51)	(51, 53)	≥53
X_3	<5.0	(5.0, 9.0)	(9.0, 12.0)	(12.0, 15.0)	>15.0
X_4	<12	(12, 18)	(18, 24)	(24, 30)	≥30
X_5	<1	(1, 2)	(2, 2.5)	(2.5, 3)	≥3
X_6	<0.5	(0.5, 0.7)	(0.7, 0.85)	(0.85, 1)	≥1
X_7	<3	(3, 5)	(5, 6)	(6, 7)	≥7

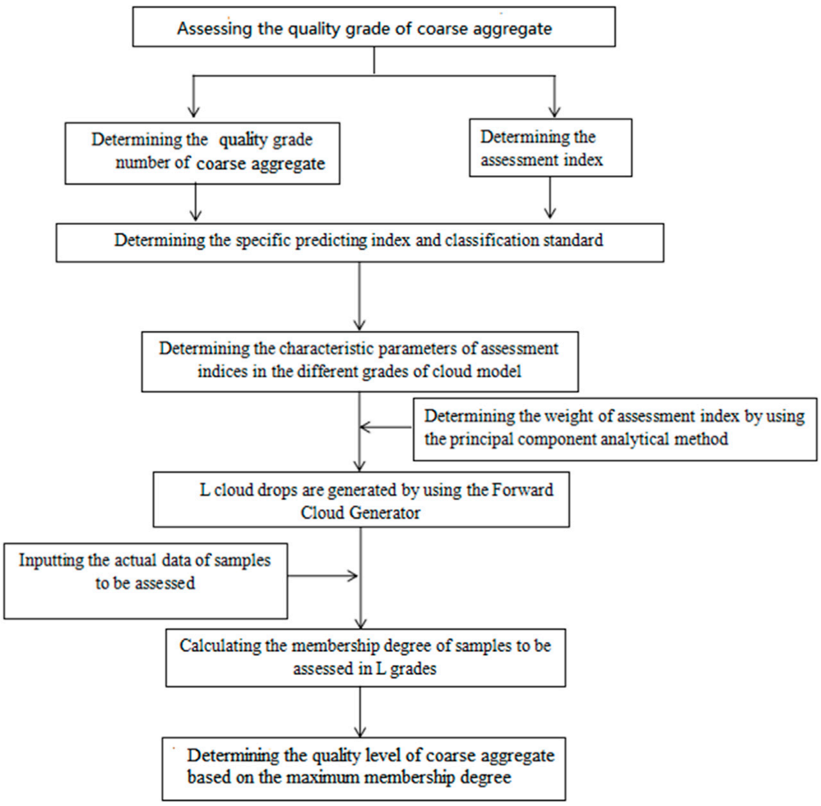

FIGURE 1
The flowchart of the assessment frame.

These indicators are quantitative ones and the seven risk assessment indicators are classified into five levels: excellent (I), good (II), medium (III), qualified (IV), and bad (V), as shown in Table 1.

3.2 The construction of the assessment frame

The quality grade of coarse aggregates not only affects the construction of concrete engineering but can also endanger human life. Consequently, evaluating the coarse aggregate quality grade of recycled concrete is essential (Chen and Li, 2008).

The flowchart of the assessment frame is plotted in Figure 1. At first, the predicting index and corresponding quality level intervals were determined and then, the weight calculation of a sample datum was performed using the principal component analytical method. Based on the classification interval of the assessment index, characteristic parameters Ex, En, and $\frac{dx^{(1)}}{dt} + ax^{(1)} = u$ were calculated in the cloud model. Finally, the synthetic membership degree

TABLE 2 Measured index values of waiting for the estimated sample.

Number of the pending judgment sample	X_1	X_2(%)	X_3(%)	X_4(%)	X_5(%)	X_6(%)	X_7(%)
1# sample	2,300	53	12	17.5	1.4	0.7	9
2# sample	2,500	50	9.2	9.8	2.4	0.5	10.2
3# sample	2,435	44	1.4	23.1	0.18	1	4.9
4# sample	2,360	46	3.1	31.6	0.43	0.4	5.8
5# sample	2,620	53	1	16	3.4	0.9	2.5

TABLE 3 The correlation coefficient matrix.

Correlation	X_1	X_2(%)	X_3(%)	X_4(%)	X_5(%)	X_6(%)	X_7(%)
X_1	1	0.237	−0.519	−0.47	0.745	0.366	−0.504
X_2	0.237	1	0.487	−0.642	0.808	0.000	0.153
X_3	−0.519	0.487	1	−0.471	0.08	−0.425	0.906
X_4	−0.47	−0.642	−0.471	1	−0.742	−0.156	−0.401
X_5	0.745	0.808	0.08	−0.742	1	0.091	−0.098
X_6	0.366	0.000	−0.425	−0.156	0.091	1	−0.568
X_7	−0.504	0.153	0.906	−0.401	−0.098	−0.568	1

TABLE 4 The accumulative contribution rate.

Component	Initial eigenvalues			Extraction sums of squared loadings		
	Total	% Of variable	Cumulative %	Total	% Of variable	Cumulative %
1	2.956	42.236	42.236	2.956	42.236	42.236
2	2.769	39.561	81.797	2.769	39.561	81.797
3	0.734	10.572	92.369			
4	0.534	7.631	100			
5	5.601×10^{-16}	8.002×10^{-15}	100			
6	1.931×10^{-16}	2.758×10^{-15}	100			
7	-9.462×10^{-18}	-1.352×10^{-16}	100			

M (shown in Eq. 17) of different samples could be obtained by using the datum to be assessed, and in combination with the weight of the assessment index. The quality grade of coarse aggregate could be determined according to the maximum certainty degree criterion.

$$M = \sum_{i=1}^{n} u_i \omega_i \tag{17}$$

3.3 The determination of index weight coefficients

The abnormal cloud model was constructed because of the randomness and fuzziness of quality assessment. To evaluate the weight coefficients of each assessment index, the original data of six assessment indexes are shown in Table 2.

Based on Eqs 1–6, and in combination with Table 2, the correlation coefficient matrix is shown in Table 3.

According to Eqs 7–9, the accumulative contribution rate of the principal component is shown in Table 4.

It can be seen in Table 4 that the accumulative contribution rate of the former two principal components arrived at 81.797%. Its magnitude was greater than 80%, so the former two principal components were selected to calculate the weight of the predicting index. According to Eq. 10, the corresponding index weight was calculated as follows.

$$\omega = \left[\, 0.0011 \;\; 0.003 \;\; 0.3894 \;\; 0.0768 \;\; 0.3619 \;\; 0.0598 \;\; 0.1079 \,\right] \tag{18}$$

TABLE 5 The digital feature of the cloud model.

Quality grade	The digital feature	X_1	X_2	X_3	X_4	X_5	X_6	X_7
I	*Ex*	2,500	23.5	2.5	6	0.5	0.25	1.5
	En	16.667	7.833	0.833	2	0.167	0.0833	0.5
	$\frac{dx^{(1)}}{dt}+ax^{(1)}=u$	0.01	0.01	0.01	0.01	0.01	0.01	0.01
II	*Ex*	2,400	48	7	15	1.5	0.6	4
	En	16.667	0.333	0.667	1	0.167	0.033	0.333
	$\frac{dx^{(1)}}{dt}+ax^{(1)}=u$	0.01	0.01	0.01	0.01	0.01	0.01	0.01
III	*Ex*	2,325	50	10.5	21	2.25	0.775	5.5
	En	8.333	0.333	0.5	1	0.0833	0.025	0.167
	$\frac{dx^{(1)}}{dt}+ax^{(1)}=u$	0.01	0.01	0.01	0.01	0.01	0.01	0.01
IV	*Ex*	2,275	52	13.5	27	2.75	0.925	6.5
	En	8.33	0.333	0.5	1	0.0833	0.025	0.167
	$\frac{dx^{(1)}}{dt}+ax^{(1)}=u$	0.01	0.01	0.01	0.01	0.01	0.01	0.01
V	*Ex*	2,225	79.5	22.5	45	4.5	1.5	10.5
	En	8.33	13.25	3.75	7.5	0.75	0.25	1.75
	$\frac{dx^{(1)}}{dt}+ax^{(1)}=u$	0.01	0.01	0.01	0.01	0.01	0.01	0.01

It was found that indexes X_3, X_5, and X_7 had a great influence on the quality grade of coarse aggregate, and the effects of the other four indices were small in comparison.

3.4 The determination of digital features in the normal cloud model

Based on Table 1, and in combination with Eqs 11–14, the classification standard of normal cloud about the coarse aggregate is depicted in Table 5.

According to Table 1, the characters of the cloud model corresponding to different indices were calculated using the forward cloud generator and are plotted in Figure 2. The horizontal coordinates represent the magnitude of other variables, whereas the vertical coordinates denote the magnitude of certainty degree. A sub-figure in Figure 2 includes five clouds, namely, I, II, III, IV, and V. When a particular variable was fixed, the certainty degree of a certain point at the state grade could be obtained.

According to Tables 2, 4, and in combination with Eqs 11, 17 18, finally, a comprehensive certainty degree was obtained, and it was compared with the actual investigation results. This is listed in Table 6.

The principal component analysis-cloud model was applied to assess the quality grade of coarse aggregate. The outcomes are shown in Table 6. As shown in Table 5, the quality grades of coarse aggregate from samples 1 to 5 were different. The stable level from samples 2 to 5 was I, which means that the quality grade of coarse aggregate in these samples was excellent, so no measurement needed to be done. The quality grade of coarse aggregate in sample 1 was V, meaning that its grade of coarse aggregate was bad and that the necessary consolidation measurement should be performed for the sample.

According to the comparative results of the different evaluation models in Table 5, it could be concluded that the outcomes assessed by the principal component analysis-cloud method were consistent with the actual investigations for five different samples; its accuracy reached 100%, which is higher than the results from the Extension Theory (80%) (Chen and Li, 2008). The conclusion was drawn that it is feasible to evaluate the quality grade of the coarse aggregate of recycled concrete using the text model.

The model not only achieved accurate results but also provided more details for the quality grade of coarse aggregate. For example, the quality grade of sample 4 more likely belonged to level I than that of samples 2 and 3 because the certainty degree of sample 4 for grade I (0.644) was higher than that of samples 2 (0.123) and 3 (0.221).

In total, the results based on the principal component analysis-cloud model could reflect the quality grade of coarse aggregate. It provides a new method and knowledge for the quality grade of coarse aggregate in the future.

3.5 Engineering example II

The regenerated fine aggregate produced by the Resource Company Limited was taken as the evaluation object. Its monitoring magnitude is listed as follows: X_1 is 2351 kg/m^3, X_2 is 4.7%, X_3 is 3.6%, X_4 is 1.33, X_5 is 0.71%, X_6 is 0.95%, and X_7 is 8.2%. The quality grade of recycled fine aggregate produced by the company was evaluated by the model in this paper; its procedure was similar to the abovementioned example and its results are shown in Table 7.

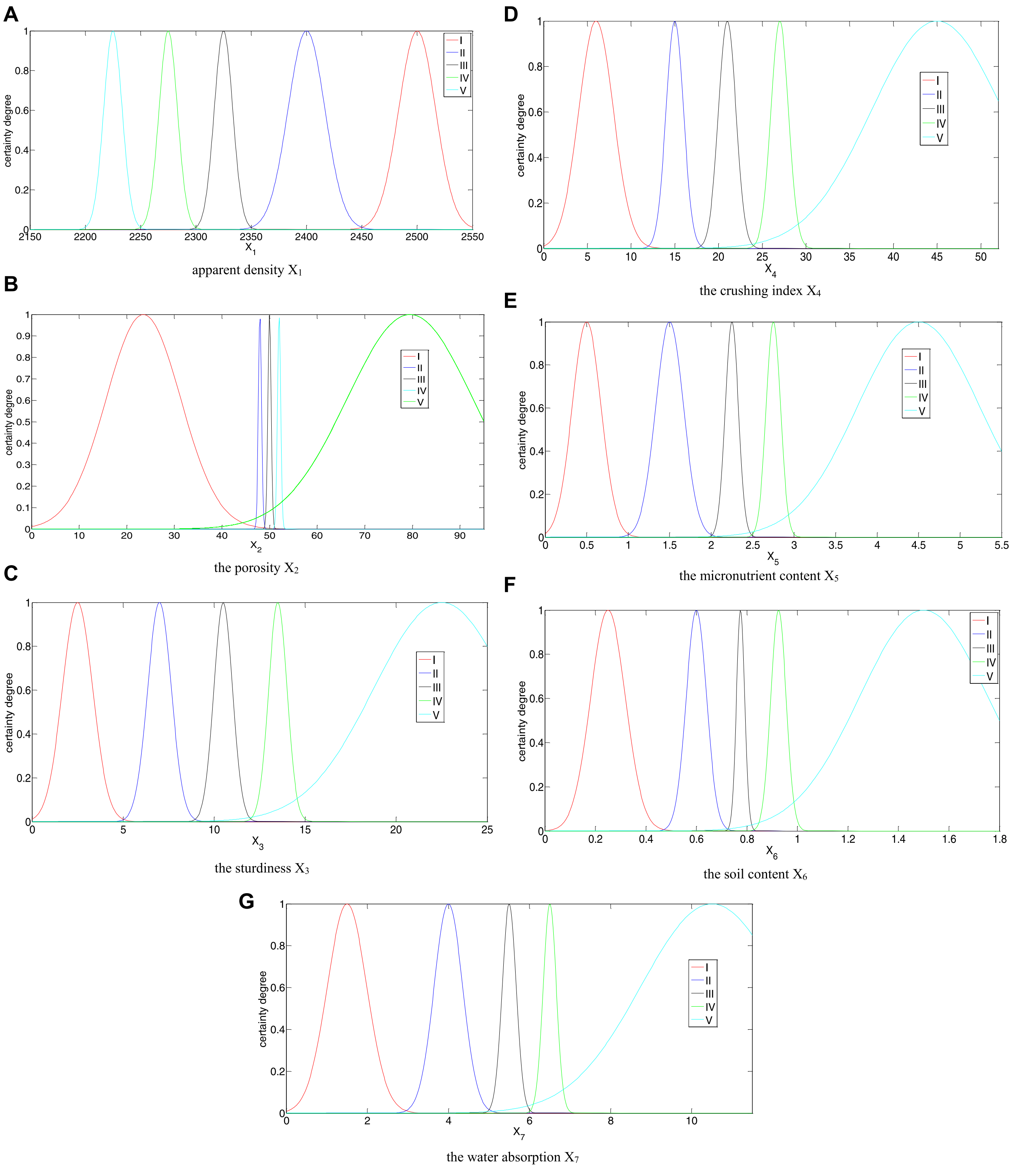

FIGURE 2
Cloud model of each assessment index.

The results obtained from Table 7 demonstrate that the suggested method is consistent with the current specification, and unascertained theory (Wan et al., 2019). The principal component analysis-cloud model is feasible for the accurate assessment of coarse aggregate quality grade of recycled concrete.

4 Conclusion

Taking into consideration the value of apparent density (X_1), porosity (X_2), sturdiness (X_3), crushing index (X_4), micronutrient content (X_5), soil content (X_6), and water absorption (X_7), a new multi-index evaluation method was introduced in this research

TABLE 6 Comprehensive certainty degree.

Sample No	The quality grade of coarse aggregate					Comprehensive assessment	Extension theory	Actual investigation
	I	II	III	IV	V			
1#sample	0	0.307	0.005	0.004	0.383	V	V	V
2#sample	0.123	0.011	0.088	0.001	0.114	I	I	I
3#sample	0.221	0.003	0.009	0.001	0.009	I	II	I
4#sample	0.644	0	0.022	0	0.019	I	I	I
5#sample	0.192	0.047	0	0.037	0.127	I	I	I

TABLE 7 Assessment results.

Evaluation method	The quality grade of coarse aggregate					Suggested model	Current specification	Unascertained theory
	I	II	III	IV	V			
results	0.25	0.4026	0.321	0.11	0.03	II	II	II

paper to evaluate the quality grade of the coarse aggregate of recycled concrete using the principal component analysis-cloud model. The different indexes' weighting coefficients were calculated using the principal component analysis method. The seismic stable level of slopes was judged using the normal-cloud model.

The present model was used for the quality grade of the coarse aggregate of recycled concrete. Finally, its outcomes were compared with the actual investigation and the calculated results obtained by using the Extension method; its accuracy reached 100%, which is higher than the results from the Extension method (80%), leading to the conclusion that it is feasible to evaluate the quality grade of the coarse aggregate of recycled concrete using the text model. It provides a new method and knowledge for the future quality grade evaluation of coarse aggregate.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

BZ: Conceptualization, Investigation, Writing–review and editing. E-WX: Funding acquisition, Validation, Writing–review and editing. X-BG: Formal Analysis, Methodology, Writing–original draft.

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Conflict of interest

Author E-WX was employed by China MCC Group Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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