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A grey comprehensive evaluation model for wheat quality incorporating PCA-EWM

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Abstract

The objective and accurate evaluation of wheat quality is the key to ensuring the safety of wheat storage. Due to the complexity and variability of wheat quality, traditional methods, such as the evaluation of single physical and chemical index, have the problems of insufficient information and poor differentiation of fuzzy intervals. Based on grey systems theory, this paper proposes a new comprehensive wheat quality grading model. Firstly, eight physical and chemical indices are selected as the factor set of the evaluation model, and the key quality indices are analyzed and screened by principal component analysis (PCA). The entropy weight method (EWM) is then used to measure the importance of the contribution of selected indices to wheat quality information. Finally, the grey evaluation model is then used to determine the grey correlation of the evaluation levels of different batches of wheat, and to rank the superiority and inferiority. The model is applied to the comprehensive analysis and evaluation of wheat samples, verifying the feasibility and validity of the model and providing some theoretical guidance for the evaluation of wheat quality.

Keywords: wheat quality; physiological and biochemical index; grey theory; comprehensive evaluation.

Practical Application: Hopefully this will be useful for food storage.

1 Introduction

Food industry is the life industry of human beings, and it is also an eternal industry. The storage environment of food industry will affect the processing quality (Lima et al., 2021). According to the Food and Agriculture Organization of the United Nations, the global loss rate of post-harvest food at the farm, transport, storage and processing stage is 13.8%, which is more than 400 billion US dollars a year. Therefore, the study of food quality changes and the search for accurate quality evaluation methods are conducive to the timely regulation of storage environment, and the improvement of food storage safety factor.

Wheat is an important food crop in the food industry. Its storage system can affect the quality (Scariot et al., 2017). Physiological and biochemical indices have long played an important role in evaluating the quality of wheat. Some of these indices change significantly with storage conditions or time, for example, fatty acid values rise rapidly with increasing storage temperature, and germination rate and peroxidase activity decrease with increasing storage time (Abdullah et al., 2019; Zhang et al., 2017a). However, there are many physical and chemical indices for wheat, which are random and unrepresentative in their selection, and a single physical and chemical index is not sufficiently informative to evaluate the quality of wheat, while the measured values of some indices are easily disturbed by the testing environment, equipment and operational specifications, affecting the accuracy of the overall quality of evaluation results (Wang et al., 2020). In addition, when multiple physical and chemical indices are used to analyze wheat quality, they are mostly limited to combining the results of multiple physical and chemical indices to analyze quality, without considering the differences in the degree of information contribution of each physical and chemical index and the complex interaction between multiple indices (Wang et al., 2018). Due to the lack of comprehensive multi-index evaluation system, it is difficult to evaluate wheat quality reasonably and reliably.

Grey system theory is a method used to deal with data with uncertain or partially missing information, it can study the characteristics and development trend of evaluation objects through a small amount of data information and make informed judgments and predictions (Zhang et al., 2017b). Among them, grey clustering and grey correlation analysis are two typical methods, they have been widely used in recent years for comprehensive evaluation problems in the fields of transportation, agriculture and environment (Li et al., 2017; Dang & Zhang, 2019). This study combines the advantages of grey clustering and grey correlation analysis, and integrates principal component analysis theory and entropy weight method. We propose a new comprehensive wheat quality evaluation mode and apply to the evaluation of wheat quality.

2. Selection of quality indices and calculation of weights

2.1 Factor sets and standardized methods

The deterioration of wheat quality is a complex process in which multiple physicochemical indices act together. As there

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are certain synergies and differences in the effects of each physicochemical index, the reasonable selection of physicochemical indices has a direct impact on the scientific accuracy of the final evaluation results. By reviewing the literature and consulting experts, and based on the ease of measurement and recognition, eight physical and chemical indices were selected as a set of wheat quality evaluation indices, and numbered, as shown in Table 1. The type of index indicates the direction of influence on the quality evaluation, the positive indices indicating that the higher the value, the better the quality, the negative indices indicating that the lower the value, the better the quality, and the intermediate indices indicating that the quality is better when the value is stable around a certain value.

The units and orders of magnitude of wheat indexes were different, in order to carry out a comprehensive analysis of these indices, the data need to be standardized. As different types of indices do not represent the same meaning, in order to facilitate the subsequent calculation and analysis, this study combined the different index types in Table 1 and used Equations 1-3 to standardize each index separately. The method is as follows:

If there are m batches of wheat and l physical and chemical index in the original dataset, the standardization matrix is $Z=(z_{ij})_{m\times l}$, (i = 1, 2, 3, ..., m; j =1, 2, 3, ..., l).

For indices a, b, g and h, the lower the value, the better the quality of the wheat.

$$\hat{x}_{ij}=\frac{x_{j\max}-x_{ij}}{x_{j\max}-x_{j\min}} \tag{1}$$

For indices as c, e and f, the higher the value, the better the quality of the wheat.

$$\hat{x}_{ij}=\frac{x_{ij}-x_{j\min}}{x_{j\max}-x_{j\min}} \tag{2}$$

Table 1. Descriptive statistics for physical and chemical indices of wheat.

No.	Physical and chemical indices	Index description	Type of index
a	Fatty acid value	An index of wheat freshness	Negative
b	Falling number	Greater impact on wheat eating quality	Negative
c	Sedimentation value	Reflects the protein content of wheat and its quality	Positive
d	Reducing sugar	Nutrients required for respiration	Intermediate
e	Germination rate	Reflects the ability to germinate under suitable conditions	Positive
f	Peroxidase	A protective enzyme against the ageing of organisms	Positive
g	Electrical conductivity	Reflects the degree of change in intracellular electrolytes	Negative
h	Malondialdehyde	End product of internal membrane lipid peroxidation in wheat	Negative

For index d, which requires stability around a desired value, the better the quality of the wheat around that value.

$$\hat{x}_{ij}=\begin{cases}\dfrac{x_{ij}-x_{j\min}}{\overline{x}_j-x_{j\min}}, & x_{ij}<\overline{x}_j\\[2ex] \dfrac{x_{j\max}-x_{ij}}{x_{j\max}-\overline{x}_j}, & x_{ij}\geq\overline{x}_j\end{cases} \tag{3}$$

where x_{ij} is the jth index of batch i, $\hat{x}_{ij}$ is the standardized index, x_{jmax} and x_{jmin} are the maximum and minimum values of index j respectively, and the ideal value of the jth index.

2.2 Establishment of a PCA-based wheat quality evaluation index set

There are complex correlations between the physical and chemical indices of wheat. If the degree of correlation between some indices and all other indices is low, it indicates that they provide a weak amount of information for the overall evaluation of quality, and when there are more factors in the evaluation index set, it will reduce the calculation efficiency of the model and increase the difficulty of the problem analysis, so it is necessary to analyze the relationship between the indices, so as to select the factors prominent in the expression of wheat quality. Related studies show that PCA has strong advantages in multivariate correlation analysis and validity verification, and without the need for a priori knowledge (Yousaf et al., 2021; Sun et al., 2020). Therefore, this paper uses PCA to analyze and select wheat physical and chemical indices of wheat, as shown in the following steps.

1)KMO and Bartlett's sphericity test.

Before factor analysis, KMO and Bartlett's spherical test are required to verify the suitability for principal component analysis (Dinata et al., 2021). The KMO value is used to compare the relationship between the simple correlation coefficient and the partial correlation coefficient between variables, PCA can be performed only when KMO value is greater than 0.5, and the closer the value is to 1, the better the analysis effect is. The Bartlett sphericity test is used to determine whether there is correlation between variables, and generally requires a significance level of a P-value less than 0.05, and also requires the cumulative contribution of the variance of the principal component factors to be no less than 70% (Zhao et al., 2019).

2)Correlation coefficient matrix calculation.

By calculating the correlation coefficient between indices C and D through Equation 4, the multi-index correlation coefficient matrix can be formed as:

$$H=\left(\frac{\operatorname{cov}(C,D)}{\sigma_C\sigma_D}\right)_{l\times l} \tag{4}$$

where C = 1, 2, 3, ..., l,D = 1, 2, 3, ..., l,cov(C, D) is the covariance, σ_C and σ_D are the standard deviations of indices C and D, respectively.

3) Cumulative variance contribution rate and index score calculation.

The principal components with a cumulative contribution rate of not less than 70% were extracted, and a maximum of t ($t < l$) principal components were selected, and the index scores in each principal component were calculated with the following Equations 5-6:

$$\alpha_{sum} = \sum_{i=1}^{t} \lambda_i \Big/ \sum_{i=1}^{l} \lambda_i \tag{5}$$

$$\delta_j = \sqrt{\lambda_i} e_{ij} \cdot \sum_{i=1}^{t} (\lambda_i \Big/ \sum_{i=1}^{l} \lambda_i) \tag{6}$$

Where λ_i is the eigenvalue of the ith principal component and e_{ij} denotes the jth value of the ith eigenvector. Finally, a comprehensive analysis of the correlation coefficient matrix and factor scores was carried out to complete a reasonable selection of indices.

2.3 Determine the index weight

The degree of influence of different physico-chemical indices on the evaluation results varies to a certain extent. In order to achieve effective differentiation, each index needs to be assigned a suitable weight. As all the physical and chemical indices of wheat can evaluate the quality to a certain extent, and as there is a lack of specific description and effective definition of the influence degree of each index on the quality in existing studies, it is necessary to take measures to allocate appropriate weights for each index. Traditional subjective weighting methods, such as hierarchical analysis (AHP), superior order diagram (PC) and Delphi have major limitations and difficult to guarantee the scientific validity of the results (Sarkar & Biswas, 2021). To avoid this problem, this study adopts the entropy weight method, an objective assignment method, to determine the weight of each index based on the amount of information provided by each index and the degree of variability. The smaller the entropy value, the greater the amount of information contained and it should be given a larger weight, and conversely the larger the entropy value, the smaller the weight should be given (Gu et al., 2021). The basic steps are as follows:

1) Let n ($j = 1, 2, 3, ..., n$) be the number of indices after filtering. The new matrix $X = (x_{ij})_{m \times n}$ is obtained by removing the redundant indices from the above standardized matrix Z, which is used as the standardized matrix for the entropy weighting method.

2) Equation 7 calculates the entropy value of each physical and chemical index.

$$E_j = -\frac{\sum_{i=1}^{m} Z_{ij} \mathrm{In} Z_{ij}}{\mathrm{In} m} \tag{7}$$

where $Z_{ij} = x_{ij} \Big/ \sum_{i=1}^{n} x_{ij}$, when $Z_{ij} = 1$, $Z_{ij}\mathrm{In}Z_{ij}=0$. The higher the value of E_j, the higher the value of the index for wheat quality evaluation.

3) Equation 8 calculates the weights of each physical and chemical index.

$$\omega_j = \frac{1 - E_j}{\sum_{j=1}^{n} (1 - E_j)} \tag{8}$$

where $\sum_{j=1} \omega_j = 1$

3 Construction of a grey comprehensive evaluation model of wheat quality

The quantitative analysis of wheat quality evaluation indices has the problem of grey numbers, and the grey levels of quality also have a certain degree of fuzziness and uncertainty, so the grey evaluation matrix can be constructed using grey system theory, and the final decision can be made. The main steps of the constructed grey comprehensive evaluation model are as follows.

3.1 Defining the rubric set and grading criteria

In order to ensure the scientific rationality of the evaluation and to meet the actual needs of the evaluation object, before evaluating the quality of wheat, it is necessary to determine the set of evaluation factors of the grey system and the number of levels of grey categories, i.e., the quality of its division into a number of levels, and give the scale criteria. Among them, the set of rubrics Q can be expressed as Equation 9:

$$Q = \{q_1, q_2, \cdots, q_d\} \tag{9}$$

where d is the number of evaluation levels, ($k = 1, 2, 3, ..., d$).

3.2 Building a grey evaluation weight vector matrix

According to the needs of quality evaluation, d grey grades are divided, i.e., corresponding to the number of evaluation levels, and then the whitening weight functions of the different grey grades are determined so that the range of grey correlation coefficient values of the wheat index dataset can be divided into d small intervals. The traditional whitening weight functions are upper limit measure, moderate measure and lower limit measure whitening weight functions, etc (Fidan & Yuksel, 2020). However, this type of whitening weight function only has affiliation with one adjacent interval, while the affiliation of the remaining n-2 intervals is 0, which will lead to the loss of much important information and affect the final quality evaluation results. To avoid this problem, this paper optimizes the traditional whitening weight function and transforms the straight-sided trapezoid of the whitening weight function into a curved-sided trapezoid, thus being able to cover all the grey grade intervals and greatly improve the utilization of information.

The whitening power functions before and after optimization are shown in Figure 1.

3.3 Building a grey correlation matrix

According to grey system theory, before evaluating the quality of wheat using multiple physical and chemical indices, the ideal assessment value of each physical and chemical index needs to be selected as the reference series, noted as $x_0(j)$. If all the indices in batch i of wheat belong to the kth grey grade, then the batch can be evaluated as the kth grade, at this time for any index j with $x_0(j) = 1$, then the reference series can be expressed as $x_0(j) = [x_0(1), x_0(2), x_0(3), ..., x_0(n)] = [1, 1, 1, ..., 1]$. The set of physical and chemical indices involved in the evaluation can be expressed as $x_i(j) = [x_i(1), x_i(2), x_i(3), ..., x_i(n)]$. In addition, the value of the resolution factor ρ needs to be set. The value of ρ is taken in the range [0,1], the closer ρ is to 1 means that the resolution of the correlation coefficient is larger, and vice versa if the resolution is smaller, generally taking the value 0.5 (Zhou et al., 2021). Then, the grey correlation coefficient between each evaluation index and the reference series can be expressed as Equation 10:

$$\varepsilon_k(j) = \frac{\min\min\left|x_0(j) - x_k(j)\right| + \rho \max\max\left|x_0(j) - x_k(j)\right|}{\left|x_0(j) - x_i(j)\right| + \rho \max\max\left|x_0(j) - x_i(j)\right|} = \frac{\min\min\left|1 - x_k(j)\right| + \frac{1}{2}\max\max\left|1 - x_k(j)\right|}{\left|1 - x_k(j)\right| + \frac{1}{2}\max\max\left|1 - x_k(j)\right|} \tag{10}$$

where min min() and max max() are the minimum and maximum differences of the whitening function matrix, respectively.

As a result, the grey correlation coefficient matrix U_i for batch i wheat index data can be expressed as Equation 11:

$$U_i = \begin{bmatrix} \varepsilon_1(1)_i & \varepsilon_2(1)_i & \cdots & \varepsilon_d(1)_i \\ \varepsilon_1(2)_i & \varepsilon_2(2)_i & \cdots & \varepsilon_d(1)_i \\ \vdots & \vdots & \ddots & \vdots \\ \varepsilon_1(n)_i & \varepsilon_2(n)_i & \cdots & \varepsilon_d(n)_i \end{bmatrix} \tag{11}$$

3.4 Determining the evaluation level and ranking degree

The combined clustering coefficients for the quality of each batch of wheat were obtained by taking the weights of each grey grade and the weights of each physicochemical index for each batch of wheat and synthesizing them by means of Equation 12.

$$Y_i = \omega_j \cdot U_i = [\omega_1 \quad \omega_2 \quad \cdots \quad \omega_n] \cdot \begin{bmatrix} \varepsilon_1(1)_i & \varepsilon_2(1)_i & \cdots & \varepsilon_d(1)_i \\ \varepsilon_1(2)_i & \varepsilon_2(2)_i & \cdots & \varepsilon_d(1)_i \\ \vdots & \vdots & \ddots & \vdots \\ \varepsilon_1(n)_i & \varepsilon_2(n)_i & \cdots & \varepsilon_d(n)_i \end{bmatrix} = [y_1 \quad y_2 \quad \cdots \quad y_d] \tag{12}$$

Using the formula $y_i = y_i \Big/ \sum_{i=1}^{j} y_i$ to normalize each integrated clustering coefficient in matrix Y_i and determine the grey grade attribute to which each batch of wheat belongs according to the principle of maximum affiliation, i.e., the quality evaluation result for that batch of wheat.

In addition, in order to obtain the ranking of the quality of each batch of wheat, from the lowest to the highest rank, corresponding to the weights 1, 2, ..., g, the ranking degree of each batch of wheat is calculated using Equation 13, thus achieving a comprehensive evaluation.

$$P_j = 1 \cdot y_1 + 2 \cdot y_2 + \cdots + g \cdot y_d \tag{13}$$

Finally, the quality evaluation results of each batch of wheat obtained from the evaluation model constructed in this paper are compared with the actual quality classification status and other evaluation methods for feasibility and validity analysis. The flow of the grey comprehensive evaluation model of wheat quality constructed in this paper is shown in Figure 2.

4 Evaluation examples

4.1 Experimental materials and test results

The experimental wheat variety chosen for this paper was Zhou Mai 22, cultivated by the Henan Provincial Academy of Agricultural Sciences. The cleaned wheat was packed in gauze in 500 g packs and placed in an artificial climate incubator for simulated storage at a temperature of about 25 °C. Samples were taken at several different storage times to test the values of the physical and chemical indices of wheat, and each index was tested based on the following:

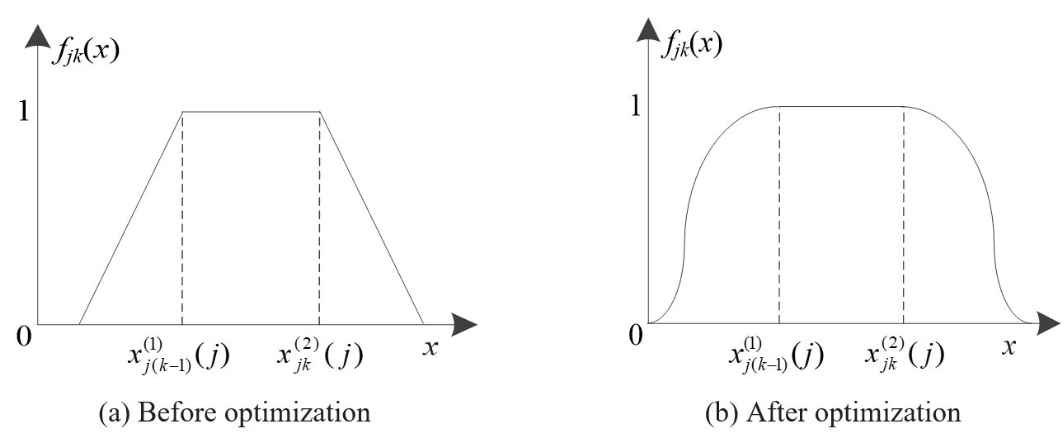

Figure 1. Images of the whitening power function before and after optimization.

Fatty acid value: GB/T 15684-2015

Landing value: GB/T 10361-2008

Sedimentation value: GB/T 21119-2007

Reducing sugar: GB/T 5009.7-2016

Germination rate: GB/T 5520-2011

Peroxidase: GB/T 32102-2015

Malondialdehyde: GB 5009.181-2016

Electrical conductivity: SL 78-1994

To avoid possible measurement errors, three parallel experiments were carried out on each batch of wheat samples for each index and the average value was taken as the test result, which resulted in the physical and chemical index data for 15 batches of wheat, as shown in Table 2.

4.2 Selection of evaluation indices

The amount of information provided by each physical and chemical index of wheat for the evaluation of overall quality varies greatly and reflects different quality conditions. In order to select the best index and at the same time reduce the

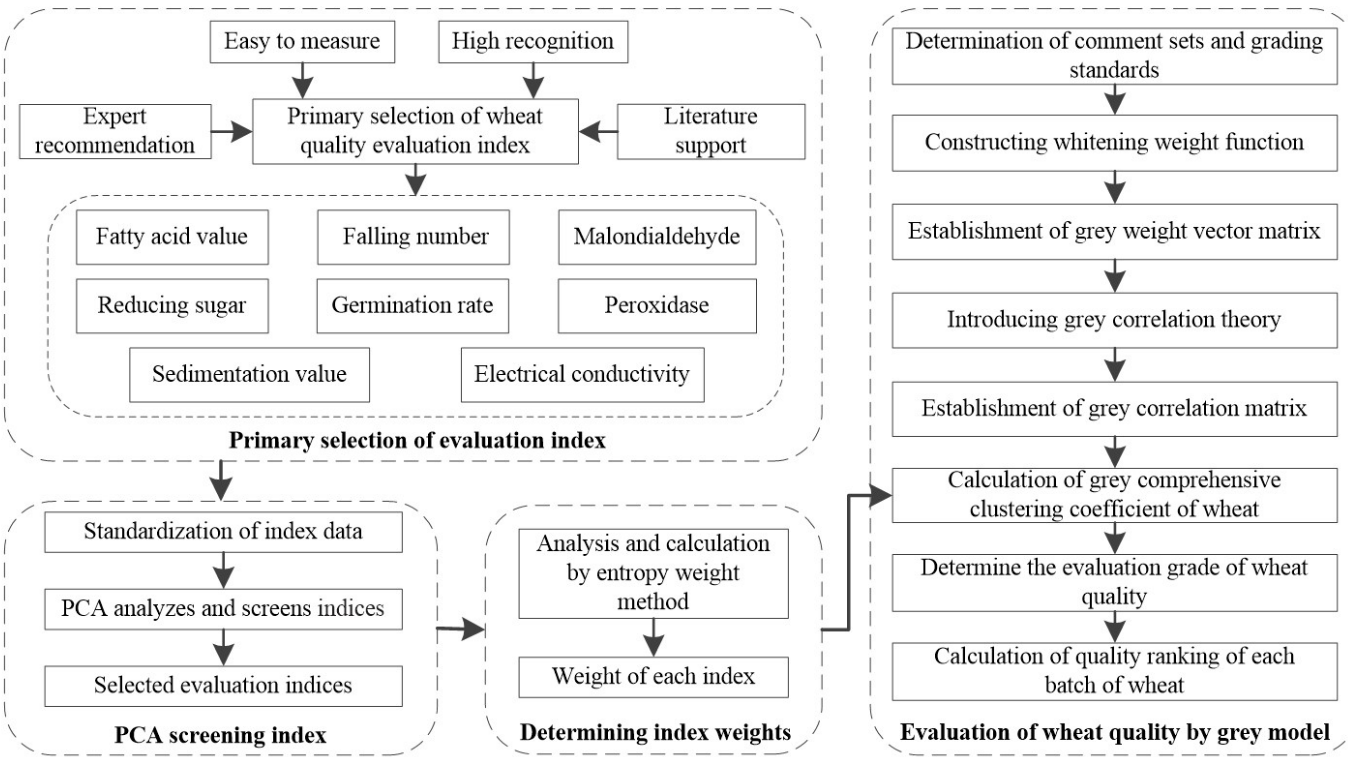

Figure 2. Modeling process for comprehensive wheat quality evaluation.

Table 2. Wheat physical and chemical index test data.

Batch	*a*/(mgKOH/100g)	*b/s*	*c/mL*	*d/%*	*e/%*	*f/(U/g)*	*g/(μs/cm/g)*	*h/(μmol/g)*
1	16	380	57	0.275	89	4000	26	2.95
2	17	330	62	0.275	90	3950	31	2.9
3	22.5	495	50	0.274	93	3000	43	3
4	23	415	55	0.28	92	3600	30	2.99
5	27	510	48	0.29	82	2600	52	3
6	16	345	60	0.27	93	4200	28	2
7	20	385	58	0.273	88	3900	25	2.75
8	24	430	49	0.276	87	3300	32	3.1
9	26	495	51	0.288	85	2750	42	3.4
10	30	495	50	0.288	80	2800	48	3.2
11	15	340	61	0.27	91	4000	25	2.8
12	18	360	59	0.27	93	4100	29	2.8
13	21	405	56	0.286	91	3800	27.5	3
14	25	330	61	0.286	89	3300	45	2.9
15	29	485	52	0.295	78	2940	40	3.3

computational complexity of the model, analysis and screening were carried out by PCA. The data of the physical and chemical indices in Table 1 were standardized using Equations 1 to 3 to obtain the standardization matrix *Z*. The KMO and Bartlett's spherical test of the multi-index matrix *Z* was performed by the SPSS data analysis tool and KMO = 0.778, $p < 0.05$, indicating that the data could be used for PCA analysis. The correlation between the indices was calculated using Equation 4 and formed the correlation matrix *H*, as shown in Table 3. The correlation coefficient takes values between [-1, 1]. The closer the value of the correlation coefficient is to 1, the more similar the two indices are, while a negative number indicates that the two indices are negatively correlated, and when it reaches -1, the two indices are inversely correlated.

The correlation coefficients between fatty acid value, landing value, sedimentation value, germination rate, peroxidase, electrical conductivity and malondialdehyde were all greater than 0.5, indicating that these indices had strong similarity in reflecting a certain quality aspect of wheat. The correlation coefficients between reducing sugar and the indices were negative and the absolute values were less than 0.5, indicating that reducing sugars were negatively correlated with the other indices and that the quality of wheat reflected a greater difference than the other indices. Therefore, the physical and chemical index of reducing sugar could be removed, and the seven other physical and chemical indices with high similarity, which can effectively reflect the quality of wheat, could be selected as evaluation factors of the model.

Following the above calculation method, the maximum combined clustering coefficients and the grey grades to which the remaining 14 batches of wheat belong can be obtained, and the results of the quality evaluation grades for each batch of wheat are shown in Table 4.

This quality grading result is in general agreement with the literature (Zhou, 2019) and the evaluation and grading results of the relevant in-house experts, and has a high degree of reliability.

Table 3. Correlation matrix of physical and chemical indices for wheat.

Index	*a*	*b*	*c*	*d*	*e*	*f*	*g*	*h*
a	1.000							
b	0.782	1.000						
c	0.747	0.948	1.000					
d	-0.409	-0.185	-0.236	1.000				
e	0.783	0.645	0.584	-0.052	1.000			
f	0.910	0.874	0.831	-0.346	0.723	1.000		
g	0.819	0.686	0.625	-0.307	0.614	0.908	1.000	
h	0.674	0.639	0.598	-0.429	0.600	0.695	0.471	1.000

Table 4. Quality evaluation results of different batches of wheat.

Batch	Grey grade composite clustering coefficient				Maximum value	Evaluation level
	Grade I	Grade II	Grade III	Grade IV		
1	0.30033	0.28549	0.23258	0.18160	0.30033	Grade I
2	0.32023	0.30133	0.22103	0.15741	0.32023	Grade I
3	0.16144	0.24646	0.30513	0.28696	0.30513	Grade III
4	0.24828	0.28293	0.26315	0.20565	0.28293	Grade II
5	0.17302	0.22213	0.28877	0.31608	0.31608	Grade IV
6	0.32180	0.29531	0.21915	0.16374	0.32180	Grade I
7	0.27390	0.27544	0.24955	0.20110	0.27544	Grade II
8	0.20626	0.27353	0.27811	0.24210	0.27811	Grade III
9	0.15998	0.23026	0.30071	0.30904	0.30904	Grade IV
10	0.17577	0.22594	0.28727	0.31102	0.31102	Grade IV
11	0.31792	0.28830	0.22218	0.17160	0.31792	Grade I
12	0.31204	0.29996	0.22632	0.16169	0.31204	Grade I
13	0.27076	0.28111	0.25371	0.19442	0.28111	Grade II
14	0.23367	0.26617	0.26805	0.23210	0.26805	Grade III
15	0.18212	0.23992	0.28591	0.29205	0.29205	Grade IV

4.3 Analysis of evaluation results

To further compare the superiority-inferiority relationships of different batches of wheat, and to verify the reasonableness and accuracy of the results of wheat quality evaluation by the model in this paper, the ranking degree of each batch of wheat was measured using Equation 13 to obtain the ranking results of each batch of wheat quality by the PCA-EWM-grey system (GS) evaluation model constructed in this paper. Meanwhile, the PCA-EWM-TOPSIS evaluation model (Liu et al., 2021) and PCA-rank sum ratio (RSR) evaluation model (Lu et al., 2022) were used as comparative models to calculate and rank the superiority and inferiority relationships of each batch of wheat, respectively. Among them, the PCA-EWM-TOPSIS evaluation model used the similarity proximity C as the scoring basis, and the PCA-RSR evaluation model used the RSR value as the scoring basis. The results of the comparative analysis of the different evaluation models are shown in Table 5.

For the PCA-EWM-GS comprehensive evaluation model constructed in this paper, according to the ranking degree relationship, it can be seen that Batch 2 wheat obtained a maximum value of 2.78438, indicating the best quality of this batch, while Batch 9 wheat scored only 2.24116, indicating the poor quality of this batch. Comparing the results with the grading results, it can be seen that the ranking of the wheat batches corresponds to the order of the evaluated grades, except for Batch 3, which belongs to Grade III, which has a slightly lower ranking score than Batch 15, which belongs to Grade IV. The reason for this is that the grey category coefficients for Batch 3, which belonged to Grade I, were lower than those for Batch 15, and a higher weight was given to the grey category coefficients for Grade I in the calculation using Equation 13. Overall, the ranking degree results verify that the model has a high degree of confidence.

In order to better analyze the relationship between the results of this model and the results of other methods, the Spearman rank correlation coefficient method (van der Walt & Fitchett, 2021) was used to discriminate the correlation between the evaluation results of this model and those of other models, which was calculated as shown in Equation 14. It is generally believed that the greater the sum of the correlation coefficients, the higher the consistency of the evaluation results between the methods, and the model's results can be considered to have a high degree of confidence.

Table 5. Comparative analysis of different evaluation models.

Batch	PCA-EWM-GS evaluation model		PCA-EWM-TOPSIS evaluation model		PCA-RSR evaluation model	
	Evaluation value	Sort	Evaluation value	Sort	Evaluation value	Sort
1	2.70455	5	0.768	5	0.824	5
2	2.78438	1	0.882	3	0.889	3
3	2.28236	12	0.331	11	0.426	11
4	2.57386	8	0.583	9	0.668	8
5	2.25209	14	0.1	15	0.139	15
6	2.77517	2	0.91	2	0.937	2
7	2.62212	7	0.733	6	0.775	6
8	2.44395	10	0.41	10	0.486	10
9	2.24116	15	0.224	12	0.299	12
10	2.26646	13	0.112	14	0.165	14
11	2.75254	4	0.923	1	0.94	1
12	2.76237	3	0.839	4	0.877	4
13	2.62821	6	0.657	7	0.732	7
14	2.50139	9	0.636	8	0.641	9
15	2.31211	11	0.219	13	0.245	13

Table 6. Correlation coefficients between different models.

Evaluation model	PCA-EWM-GS evaluation model	PCA-EWM-TOPSIS evaluation model	PCA-RSR evaluation model
PCA-EWM-GS evaluation model	1	0.939	0.943
PCA-EWM-TOPSIS evaluation model	0.939	1	0.996
PCA-RSR evaluation model	0.943	0.996	1

$$r = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \tag{14}$$

where n is the total batches of wheat and d_i is the difference in ranking of the evaluation results between the models for the i^{TH} batch of wheat. The correlation coefficients between the evaluation results of different models are shown in Table 6.

Comparing the results of the other two evaluation models, we can find that the ranking results of each batch of wheat quality are basically consistent, and the ranking results of different evaluation models for each batch of wheat have less than 3 digits difference. The correlation coefficients between the results of the evaluation models were all greater than 0.9, indicating that the results of the three evaluation models were significantly correlated, which indicates that the evaluation results of the models are highly consistent and validates the reasonableness and validity of the calculation results of the model constructed in this paper. In addition, a closer look at the above table shows that the results of the PCA-EWM-TOPSIS evaluation model and the PCA-RSR evaluation model are closer, with a correlation coefficient of 0.996, while the correlation coefficient between PCA-EWM-GS evaluation model and the two comparative models is slightly smaller, which is mainly due to the fact that the PCA-EWM-TOPSIS evaluation model is used to determine the positive and negative ideal values of each index and the optimal solution, and ranking the batches of wheat according to their proximity to the optimal solution, whereas the PCA-RSR method is based on the RSR, a dimensionless statistic, through the conversion of rank. Both of these comparison models only analyze the intrinsic relationship between the index data and make judgments on the results, while ignoring the influence of the fuzzy grey grade boundary value of the indices on the ranking results, which may have certain limitations in practical application. In contrast, the ranking results of the model established in this paper are more scientific and effective, and better meet the practical needs.

5 Summary

In response to the shortcomings of insufficient information and low accuracy in evaluating wheat quality by single indices, this paper constructs a multi-index wheat quality grey comprehensive evaluation model based on a grey comprehensive evaluation model and combining the PCA and entropy weight method. The analysis method in this paper further enriches the theoretical knowledge of the grey comprehensive evaluation model and provides a new way for the comprehensive evaluation of wheat quality.

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