Composition analysis of glass products based on correlation analysis

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Abstract: The main raw material of glass is quartz sand, and the main chemical composition is silica (SiO_2). Due to the high melting point of pure quartz sand, in order to reduce the melting temperature, it is necessary to add flux in refining. The main chemical composition varies with the flux added. By comparing the chemical composition statistics of high-potassium glass and lead-barium glass before and after weathering, it is found that SiO_2 content of high-potassium glass increases after weathering, while lead-barium glass increases after weathering. The content of SiO_2 decreased after weathering. From the mapping relationship before and after weathering, the content of each chemical component before differentiation was calculated. The correlation of chemical components between high potassium and lead and barium glasses can be seen by Pearson correlation coefficient. By grey correlation analysis, it can be seen that lead oxide and barium oxide are the main factors to distinguish the two types of glass. Lead barium contains more lead oxide and barium oxide than high potassium, and high potassium contains more potassium oxide than lead barium.

Keywords: Pearson correlation coefficient, mapping, grey correlation analysis, component prediction

1. Introduction

The main raw material of glass is quartz sand, the main chemical composition is silica (SiO_2). Due to the high melting point of pure quartz sand, in order to reduce the melting temperature, it is necessary to add flux in refining. The fluxers commonly used in ancient times include plant ash, natural natron, saltpeter and lead ore, etc., and limestone is added as a stabilizer, which is converted into calcium oxide (CaO) after calcination. The main chemical composition varies with the flux added [1].

In this paper, the surface of different types of glass cultural relics are statistically analyzed with or without weathering chemical composition content, and the chemical composition content before weathering is predicted according to the weathering point detection data. In addition, the relationship between the chemical components of different categories of glass cultural relics was analyzed, and the difference of the relationship between the chemical components of different categories was compared.

2. Model Establishment

2.1. Statistical Analysis

SPSS was used for descriptive statistics to calculate the statistical rule before hyperkalemia differentiation. Data visualization was conducted to analyze the changing trend of the components before and after weathering.

2.2. Data Mapping

The data mapping expression can be expressed by Eq (1):

$$\frac{x_i}{Max_{Before\ weathering} - Min_{Before\ weathering}} = \frac{y_i}{Max_{After\ weathering} - Min_{After\ weathering}} \quad (1)$$

x_i(i=1, 2……14) is the expression of each component before differentiation, y_i(i=1, 2……14)is the expression of each component after differentiation. $Max_{Before\ weathering}$ represented the maximum chemical composition content before weathering, $Max_{After\ weathering}$ represented the maximum chemical composition content after weathering, $Min_{Before\ weathering}\ and\ Min_{After\ weathering}$ represented the minimum chemical composition content before and after weathering, respectively [2,3].

2.3. Correlation degree test

2.3.1 Correlation analysis: Pearson correlation coefficient

Pearson correlation coefficient was used for correlation analysis [4]. Pearson's correlation coefficient (Eq 2) can be obtained by estimating the covariance and standard deviation of the sample, which is commonly represented by *r* [5]. Correlations are shown in Table 1.

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \quad (2)$$

Table 1. Pearson correlation description

Correlation coefficient	Correlation
0.8-1.0	Highly relevant
0.6-0.8	Strong correlation
0.4-0.6	Medium related
0.2-0.4	Weak correlation
0.0-0.2	Very weakly correlated or uncorrelated

2.3.2 Grey Correlation Analysis

In the process of system development, if the change trend of two factors tends to be the same, that is, the synchronous change degree of the two factors is higher, that is, the correlation degree of the two factors is higher. Otherwise, it is lower [6,7]. Therefore, grey correlation analysis method is usually based on the degree of similarity or dissimilarity between the development trend of factors, such as the comparison of the similarity between the geometric relationship of data series and the geometric shape of curves, which is a method to measure the degree of correlation between factors [8,9].

Step 1: characteristic sequence and parent sequence.

Step 2: Unify the dimensions of the index data. Eliminate the influence caused by the different units of each index and the great difference between the numerical orders of magnitude, and avoid the occurrence of unreasonable phenomena.

Step 3: Calculate the correlation coefficient. The correlation coefficient between each comparison sequence and the corresponding element of the reference sequence is calculated from Eq (3): ρ is the resolution coefficient, and the value is within (0,1). The smaller the resolution coefficient, the greater the difference between the correlation coefficients and the stronger the discrimination ability, usually 0.5.

Step 4: Calculate the association order. The weighted average of the correlation coefficients between each index and the corresponding elements of the reference sequence is calculated to reflect the correlation between each manipulation device object and the reference sequence, which is called the correlation degree. Remember to Eq (3):

$$r_{0i} = \frac{1}{m}\sum_{k=1}^{m} W_k \zeta_i(k) \tag{3}$$

Step 5: Analyze the calculation results. According to the grey weighted correlation degree, the correlation order of each evaluation object is established. The greater the correlation degree, the more important the evaluation object is to the evaluation standard (Eq 4).

$$\gamma\left(x_0(k), x_i(k)\right) = \frac{\triangle min + \rho \triangle max}{\triangle_{ik} + \rho \triangle max}$$
$$\triangle min = \min_i \min_k |x_0(k) - x_i(k)|$$
$$\triangle max = \max_i \max_k |x_0(k) - x_i(k)| \tag{4}$$
$$\triangle_{ik} = |x_0(k) - x_i(k)|$$

3. Result Analysis

3.1. Change trend of composition before and after weathering

Table 2 and Figure 1 show the mathematical statistical data and visual pictures of the components of different kinds of glass before and after weathering. It can be seen that for the high potassium type, the silica content increases after weathering. But for lead and barium, silica content decreases after weathering.

Table 2. Statistical mathematical quantities of high potassium before weathering

	Sample size	Max	Min	Mean	Standard deviation	Median	Variance
SiO_2	12	87.05	59.01	67.984	8.755	65.53	76.652
K_2O	12	14.52	0	9.331	3.92	9.83	15.369
SnO_2	12	2.36	0	0.197	0.681	0	0.464
CuO	12	5.09	0	2.452	1.66	2.345	2.756
SO_2	12	0.47	0	0.102	0.186	0	0.034
SrO	12	0.12	0	0.042	0.048	0.02	0.002
BaO	12	2.86	0	0.598	0.982	0	0.965
P_2O_5	12	4.5	0	1.402	1.434	1.02	2.056
PbO	12	1.62	0	0.412	0.589	0.155	0.347
Al_2O_3	12	11.15	3.05	6.62	2.492	6.185	6.208
Fe_2O_3	12	6.04	0	1.932	1.667	2.11	2.778
MgO	12	1.98	0	1.079	0.676	1.165	0.457
Na_2O	12	3.38	0	0.695	1.287	0	1.656
CaO	12	8.7	0	5.333	3.092	6.095	9.563

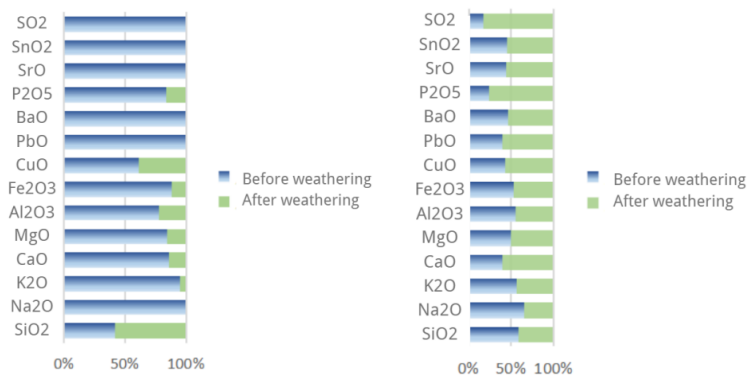


Fig. 1 Comparison of high potassium and lead-barium glasses before and after weathering

3.2. Composition prediction before weathering

The composition prediction of some glass relics before weathering is shown in Table 3.

Table 3. Composition prediction before weathering

Sampling sites	SiO_2	Na_2O	K_2O	CaO
2.00	67.22	0.00	1.70	0.85
7.00	75.59	0.00	0.00	7.03
8.00	47.78	0.00	0.00	0.69
9.00	73.35	0.00	11.64	3.86
10.00	74.48	0.00	18.10	1.30

Sampling sites	MgO	Al_2O_3	Fe_2O_3	CuO	PbO
2.00	1.05	7.24	1.75	0.13	19.53
7.00	0.00	7.51	1.27	5.68	0.00
8.00	0.00	2.17	0.00	6.72	15.12
9.00	0.00	4.74	2.26	2.57	0.00
10.00	0.00	2.90	1.83	1.39	0.00

Sampling sites	BaO	P_2O_5	SrO	SnO_2	SO_2
2.00	0.00	0.43	0.10	0.00	0.00
7.00	0.00	2.92	0.00	0.00	0.00
8.00	26.45	0.55	0.24	0.00	0.28
9.00	0.00	1.58	0.00	0.00	0.00
10.00	0.00	0.00	0.00	0.00	0.00

3.3. Relationship between chemical components

The correlation between chemical components of different types of glass cultural relics is shown in Figure 2,3. The composition content of high-potassium glass and lead-barium glass is compared as shown in Figure 4, indicating that the content of lead oxide and barium oxide is quite different.

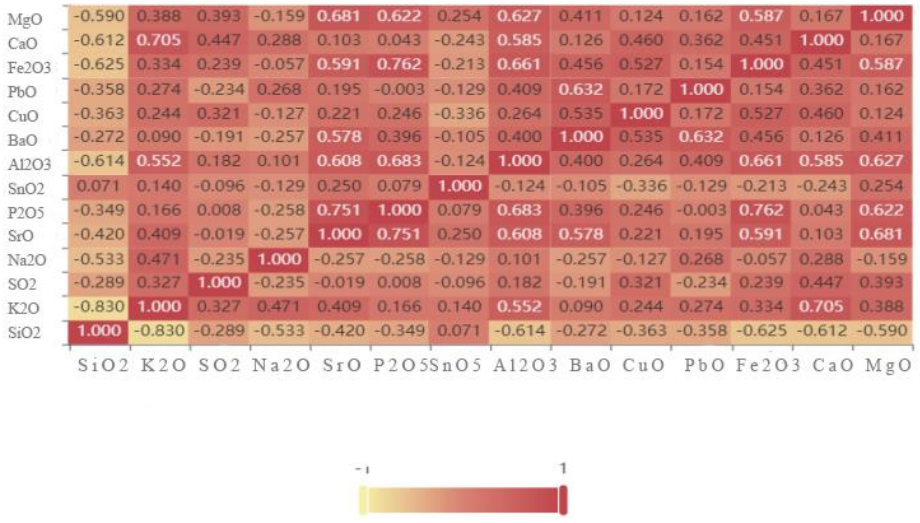


Fig. 2 Correlation coefficient thermogram of high potassium glass composition

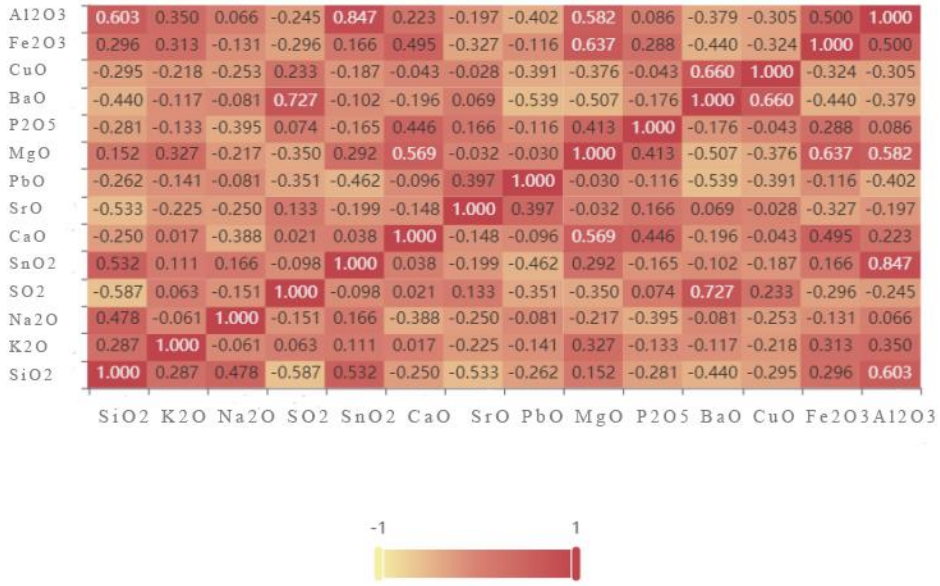


Fig. 3 Correlation coefficient thermogram of lead-barium glass composition

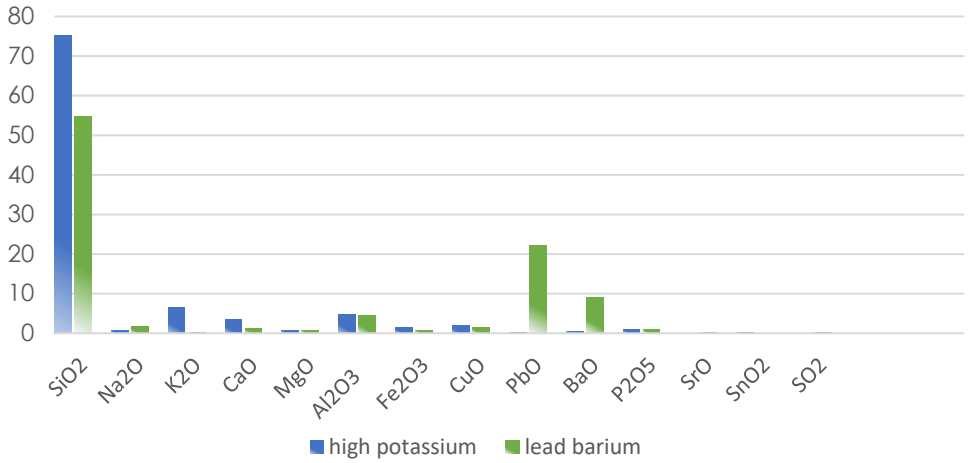


Fig. 4 Composition comparison of high potassium and lead barium glass

The gray correlation results (Table 3) were obtained by assigning high price and lead-barium type glass with values of 0 and 1. It can be seen that the correlation degree between lead oxide and barium oxide is the highest. By referring to the [3] and the known subject information, it can be seen that lead-barium glass contains more lead oxide and barium oxide, which is consistent with the conclusion of this section [10,11].

Table 4. Grey correlation results of glass composition content

Item	PbO	BaO	SrO	SO2	Na2O	P2O5	Al2O3	MgO	SiO2	CuO	Fe2O3	SnO2	CaO	K2O
Correlation degree	1	0.949	0.871	0.651	0.641	0.517	0.497	0.477	0.466	0.462	0.439	0.413	0.410	0.342
Ranking	1	2	3	4	5	6	7	8	9	10	11	12	13	14

4. Conclusion

In this paper, through statistical analysis and correlation analysis, the composition of different types of glass before and after weathering is compared, and the relationship between components is analyzed. The results show that the content of SiO_2 in high-potassium glass increases after weathering, while the content of SiO_2 in lead-barium glass decreases after weathering. Lead oxide and barium oxide are the main factors that distinguish the two types of glass. Lead barium contains more lead

oxide and barium oxide than high potassium, and high potassium contains more potassium oxide than lead barium.

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