Study on Composition Analysis and Species Identification of Glass Relics Based on the Multiple Linear Regression Model

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Abstract: Antique glass products are highly susceptible to environmental influences and weathering, and their chemical composition ratios are prone to change. Given this, this article is based on integrating known data processing and mathematical methods such as comprehensive evaluation and mean analysis to establish a multiple linear regression model to explore the changes in surface chemical composition. According to the clustering analysis method, accurately classify subcategories and explore the rationality and sensitivity of the classification results. Finally, use Euclidean distance to determine the unknown category of cultural relics to be tested. The results show that: (1) For lead barium glass, Na_2O and Al_2O_3 have a protective effect on weathered cultural relics, and the SiO_2 content decreases after weathering, while the PbO, BaO, P_2O_5, and CaO content increases; For high potassium glass, the content of SrO, SnO, and SO_2 is almost zero, and the content of Na_2O remains unchanged before and after weathering. The content of SiO_2 increases while the content of other elements decreases. (2) The model successfully subdivided the glass subclass into four categories: low SiO_2, BaO-PbO-CuO, high PBO high BaO-SO_2, low BaO high PbO-SiO_2, and high SiO_2-PbO low BaO-Al_2O_3. Three types of high potassium glass: high SiO_2, low SiO_2, SiO_2-CaO-Al_2O_3.

Keywords: Glass artifacts; Weathering; Comprehensive evaluation; Multiple linear regression; System clustering method; Euclidean distance

1. Introduction

Glass is precious physical evidence of trade on the Silk Road, and antique glass products are essential to ancient Chinese culture [1-2]. By analyzing the composition and identifying the types of glass products, we can better understand the characteristics of antique glass manufacturing processes and materials, provide reference and guidance for protecting and collecting cultural relics, and provide reference and inspiration for modern glass manufacturing and cultural development. At the same time, it provides important physical evidence for studying ancient society, culture, history, and other aspects better to understand antique glass manufacturing processes and material usage.

Research on glass has been ongoing since ancient times [3-4]. Albert Herder [5] revealed the main characteristics of outdated European glass manufacturing processes and material usage. One of the representative figures in the study of antique glass in the United States, American scholars Mary Kate Kerlin and Dianna Stewart, revealed the characteristics of local antique glass manufacturing processes and material usage through their analysis of antique glass products in the United States. The research achievements jointly collaborated by domestic and foreign scholars have also contributed to this field [4]. In 2008, the Chinese Palace Museum and the French National Museum jointly held the "Jingdezhen Blue and white porcelain and

European Glass Exhibition," demonstrating the charm of ancient Chinese Blue and white porcelain and European glass.

However, the above research rarely involves analyzing and identifying the composition of glass products. Based on this, this article establishes a glass product composition analysis model based on multiple regression models. This research method provides essential guidance for archaeological work and can provide vital information for studying ancient society, culture, history, and other aspects.

2. Symbol Description

The main variables and symbols involved in this article are shown in Table 1:

Table 1 Symbol Description

Symbol	Symbolic meaning
a	The differentiation rate of this feature in glass artifacts
w	Weight
x	Average value
k	Parameters of linear equation variables
x_i	Variables of linear equations

3. Model establishment

3.1 Prediction of Chemical Composition Content of Glass Before Weathering

Firstly, it was found through the integration and processing of basic information on glass relics that three types of factors influence the weathering of glass relics. The weathering rate was introduced, and a comprehensive evaluation method was used to explore the relationship between glass type a_1, decorative type a_2, color depth a_3, and surface weathering of cultural relics. Due to the varying degrees of influence and mutual independence of various factors, we consider weighting operations based on the weathering intensity between the factors in order to conduct a comprehensive evaluation.

Secondly, based on the characteristics of the data, we choose to use the mean analysis method to solve the problem. By systematically extracting data from two types of cultural relics samples, high potassium and lead barium glasses are divided into unweathered and weathered. After statistical analysis of the percentage content of chemical components, coordinate images of weathering points are obtained. At the same time, each data group is subjected to extreme value removal, and through mean analysis, the average of the data is used as the percentage of the content of that component. The trend of statistical changes is obtained by comparing the average values.

Finally, to explore the specific statistical patterns of chemical element changes within glass artifacts during the weathering process, data from two types of glass artifacts were extracted and sorted according to the percentage content of SiO_2 from high to low. The percentage content of SiO_2 was used as a measure of whether the artifacts were weathered or not. At the same time, we believe that there is a linear relationship between the percentage content of SiO_2 and the percentage content of other oxides during the weathering process of glass artifacts. Establish a multiple linear regression model by taking the percentage content of other oxides as the independent variable x_i (i=1,2,..., 13) and the percentage content of SiO_2 as the dependent variable y.

3.2 Classification method for glass subclasses

In antique glass production, differences in raw materials, fluxes, stabilizers, firing processes, and storage environments can all affect the composition and category of glass. Cultural relics can be used as samples to analyze the similarity between glass relics based on Q-type classification and systematic clustering [6]. SPSS software can be used to cluster the data of all cultural relics. At the same time, cultural relics exist as samples and can be classified using Q-type classification. The system clustering method is used to analyze the similarity between various glass cultural relics. At the same time, in this clustering analysis process, we use square Euclidean distance to measure the degree of similarity between glass cultural relics [7]. Thus achieving accurate sub category segmentation of all glass artifacts. And analyze the rationality and sensitivity of classification.

3.3 Glass Type Identification Model

When exploring the chemical composition of unknown cultural relics and identifying their types, by analyzing the data of known cultural relics, it was found that the chemical composition content measured by the Chinese material for subcategory classification is consistent. According to the law, after weathering, the SiO_2 content of high potassium glass is greater than 90, and the SiO_2 content of lead barium glass is less than 50; When undifferentiated, the mean value of high potassium glass is greater than that of lead barium glass. Draw a rough conclusion:

High potassium glass：A6，A7，A1，A8

Lead barium glass：A2，A5，A3，A4

The expression for Euclidean distance is:

$$d\left(x_i, x_j\right)=\sqrt{\sum_{k=1}^{d}\left(x_{ik}-x_{jk}\right)^2} \tag{1}$$

We use the classification system in its system clustering model and the Euclidean distance method to determine and classify the unknown cultural relic categories in Data3.

4. Result analysis

4.1 Results of solving multiple regression models based on component analysis

(1) For glass type a1, 18 samples of high potassium glass and 40 samples of lead-barium glass exist. The weathering rate of the corresponding glass type can be obtained by taking the number of the corresponding type of glass as the denominator and the number of individuals of that type of glass that have weathered as the numerator. Weathering rate of high potassium glass: is 33% Weathering rate of lead-barium glass: is 70%.

(2) There are three styles of A, B, and C for the three bell pattern type a_2. Similarly, we take the total quantity of various kinds and the internal weathering quantity to provide the weathering rate of the corresponding styles.

(3) Excluding four glass artifacts without recorded colors (corresponding numbers: 19,40,48,58) for the color depth a_3. Calculate the weathering rate of the complementary colors for the remaining 54 cultural relics, and the results are shown

in Table 2:

Table 2 Display of Calculation Results of Weathering Rate of Colors Corresponding to Cultural Relics

Number	1	2	3	4	5	6	7	8
Color	Blue Green	Light green	Purple	Dark green	Light green	Black	Dark Blue	Green
Total	15	20	4	7	3	2	7	1
Differentiation quantity	9	12	2	4	1	2	4	0
Differentiation rate	60%	60%	50%	57%	33%	100%	57%	0

Due to the varying degrees of influence of three factors on glass weathering, and their mutual independence, they collectively impact the weathering results of glass. By studying the weathering intensity among the three factors, they are weighted as w_1, w_2, and w_3 ($w_1+w_2+w_3=1$) .

We use the following equation for evaluation to determine whether the glass artifacts are weathered.

$$\mathrm{m}=\mathrm{w}_1 * a_1 + w_2 * a_2 + w_3 * a_3 \tag{2}$$

Here, we believe that $w_1=0.6$, $w_2=0.1$, $w_3=0.3$:

$$\mathrm{m}=0.6a_1+0.1a_2+0.3a_3 \tag{3}$$

We are assuming that when the weathering rate of the glass relic is m 0.5, $a_1=0.7$, $a_2=0.5$, $a_3=0.6$, m=0.65>0.5, it indicates that the glass has weathered. At the same time, the data of two types of glass relics are extracted and organized separately, divided into two groups: high potassium and lead barium glass, and then divided into two parts: unweathered and weathered within them. To obtain a universal element content percentage ratio, we perform extreme value removal and mean analysis on the data of each group of points and use the average of the obtained data as the element content [8] percentage ratio of that part. By comparing the average values, we obtain the variation trend of the statistical law and obtain the content mean-variance Table 3,6:

$$\overline{\mathrm{x}} = \frac{x_1 + x_2 + \ldots + x_\mathrm{n}}{n} \tag{4}$$

Table 3 Mean Variance of Composition Content after Weathering of High Potassium Glass

Sampling points	SiO_2	Na_2O	K_2O	CaO	MgO	Al_2O_3	Fe_2O_3	CuO	PbO	BaO	P_2O_5	SrO	SnO_2	SO_2
Average value	93.96	0.00	0.54	0.87	0.20	1.93	0.27	1.56	0.00	0.00	0.28	0.00	0.00	0.00

Standard deviation	1.73	0.00	0.45	0.49	0.31	0.96	0.07	0.93	0.00	0.00	0.21	0.00	0.00	0.00

Table 4 Mean Variance of Composition Content of High Potassium Glass Before Weathering

Sampling points	SiO_2	Na_2O	K_2O	CaO	MgO	Al_2O_3	Fe_2O_3	CuO	PbO	BaO	P_2O_5	SrO	SnO_2	SO_2
Average value	67.98	0.70	9.33	5.33	1.08	6.62	1.93	2.45	0.41	0.60	1.40	0.04	0.20	0.10
Standard deviation	8.76	1.29	3.92	3.09	0.68	2.49	1.67	1.66	0.59	0.98	1.43	0.05	0.68	0.19

Table 5 Mean Variance of Composition Content after Weathering of Lead Barium Glass

Sampling points	SiO_2	Na_2O	K_2O	CaO	MgO	Al_2O_3	Fe_2O_3	CuO	PbO	BaO	P_2O_5	SrO	SnO_2	SO_2
Average value	24.91	0.22	0.13	2.70	0.65	2.97	0.58	2.28	43.31	11.81	5.28	0.42	0.07	1.37
Standard deviation	10.61	0.56	0.24	1.66	0.71	2.63	0.74	2.82	12.23	9.98	4.20	0.26	0.27	4.21

Table 6 Mean Variance of Composition Content of Lead Barium Glass Before Weathering

Sampling points	SiO_2	Na_2O	K_2O	CaO	MgO	Al_2O_3	Fe_2O_3	CuO	PbO	BaO	P_2O_5	SrO	SnO_2	SO_2
Average value	54.66	1.68	0.22	1.32	0.64	4.46	0.74	1.43	22.08	9.00	1.05	0.27	0.05	0.16

According to Table 3-Table 6: (1) For lead barium glass, by comparing the changes in the content of various chemical elements before and after weathering, it is concluded that Na_2O and Al_2O_3 have a protective effect on weathered cultural relics. From never weathering to weathering, SiO_2 content decreases, while PbO, BaO, P_2O_5, and CaO content increases. (2) For high potassium glass, the content of Na_2O remains unchanged before and after weathering, while the content of SrO, SnO, and SO_2 is almost zero. Before and after weathering, the content of SiO2 increases while the content of other elements decreases. According to:

$$y = k + k_1 * x_1 + \ldots + k_{13} * x_{13} + e \tag{5}$$

$$\begin{aligned} y \; = \; & 100.2103 - 0.9858x_1 - 1.1101x_2 - 0.9540x_3 - 2.6657x_4 - 0.9767x_5 - 1.2706x_6 \\ & - 1.2367x_7 - 0.5281x_8 - 0.7141x_9 - 0.5782x_{10} + 13.1490x_{11} - 1.4280x_{12} - 0.6384x_{13} \end{aligned} \tag{6}$$

4.2 System clustering model solution

Since x initial categories of glass artifacts exist in the data, the length value of the default Euclidean distance in the software is used as the similarity step, and two specific similar glass crafts are classified into one category by finding the shortest stage. The most straightforward step search is performed for step 2, and the classification cycle ends when there is no search target.

The data classification was obtained by taking the appropriate distance, and according to the tree diagram, the ancient glass artifacts were classified into seven categories, lead-barium glass into four categories: high-potassium glass into three categories, and the results are shown in Table 8.

Table 8 Classification Results

Lead barium glass	High potassium glass
Low SiO_2-BaO-PbO-CuO High PBO- High BaO-SO_2 Low BaO- High PbO-SiO_2 High SiO_2-PbO- Low BaO-Al_2O_3	High SiO_2 Low SiO_2 SiO_2-CaO-Al_2O_3

For the rationality of classification, which is to determine whether the category is in line with the actual situation, and the sensitivity of classification, which is sensitivity, we measure the variety based on the error range of clustering analysis. Retrieve specific data from each of the four types and determine the degree of similarity between them. The data of each group of categories is collected and compared internally to obtain a comparison image. Due to space limitations, the fitted image is displayed as shown in Figures 1 to 4:

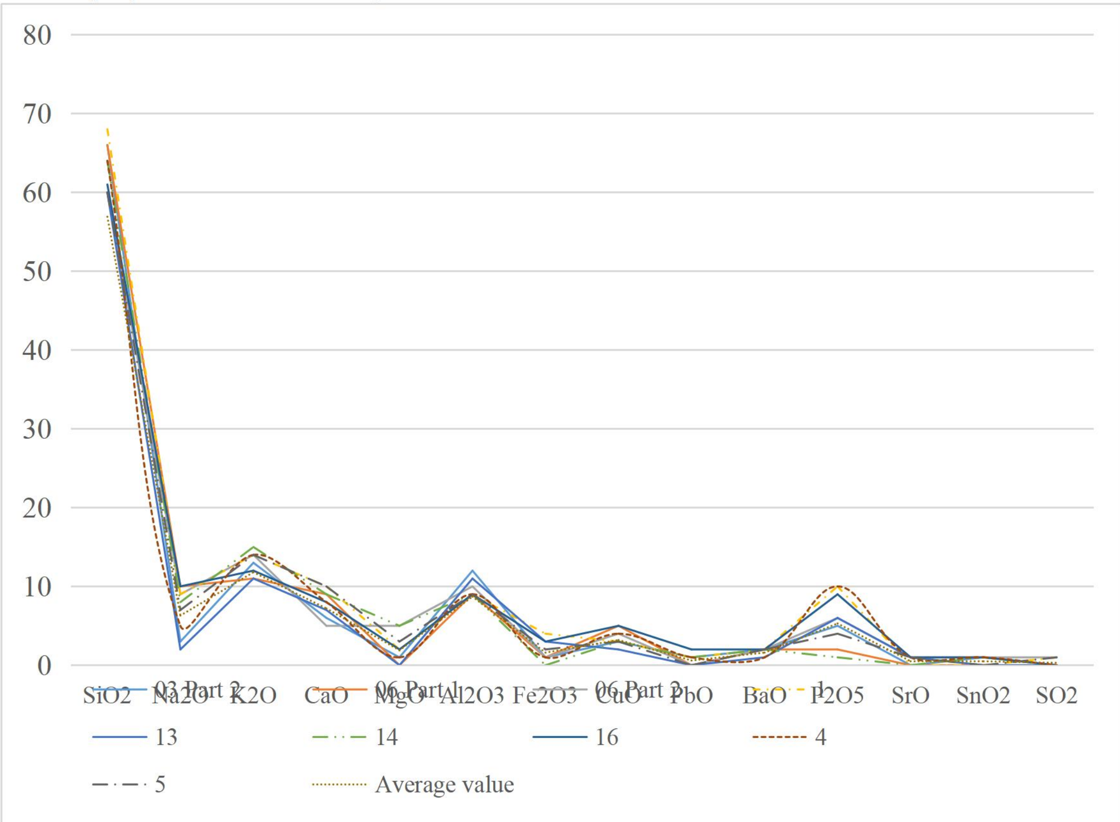

Figure 1 High potassium glass fitting curve 1

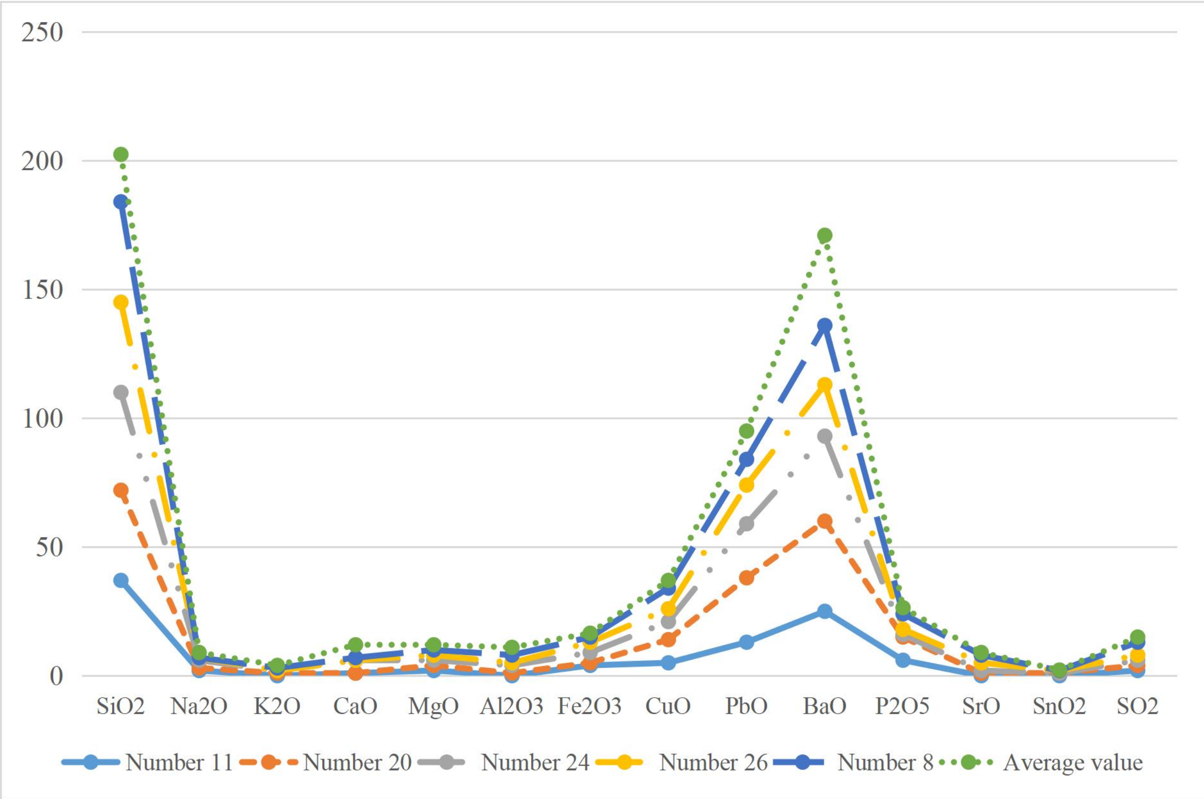

Figure 2 Lead barium glass fitting curve 1

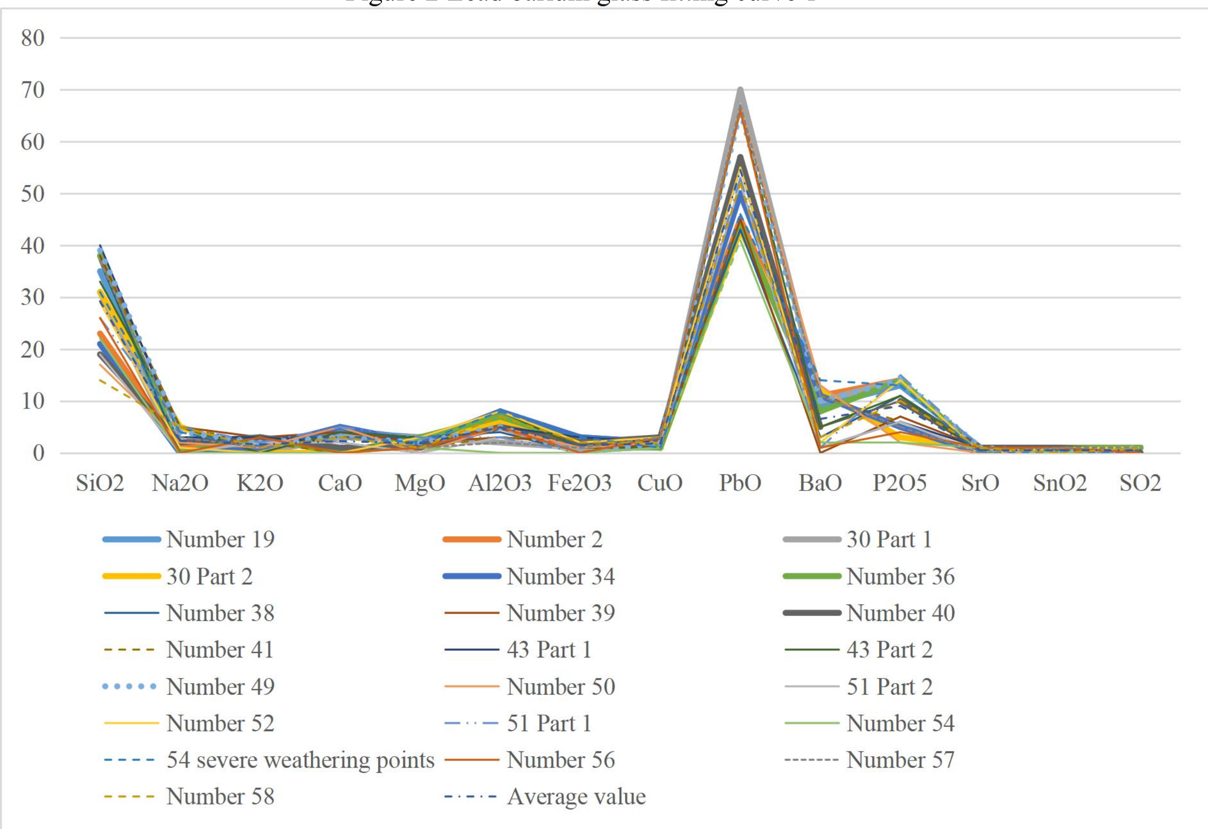

Figure 3 Fitting Curve 2 of Lead Barium Glass

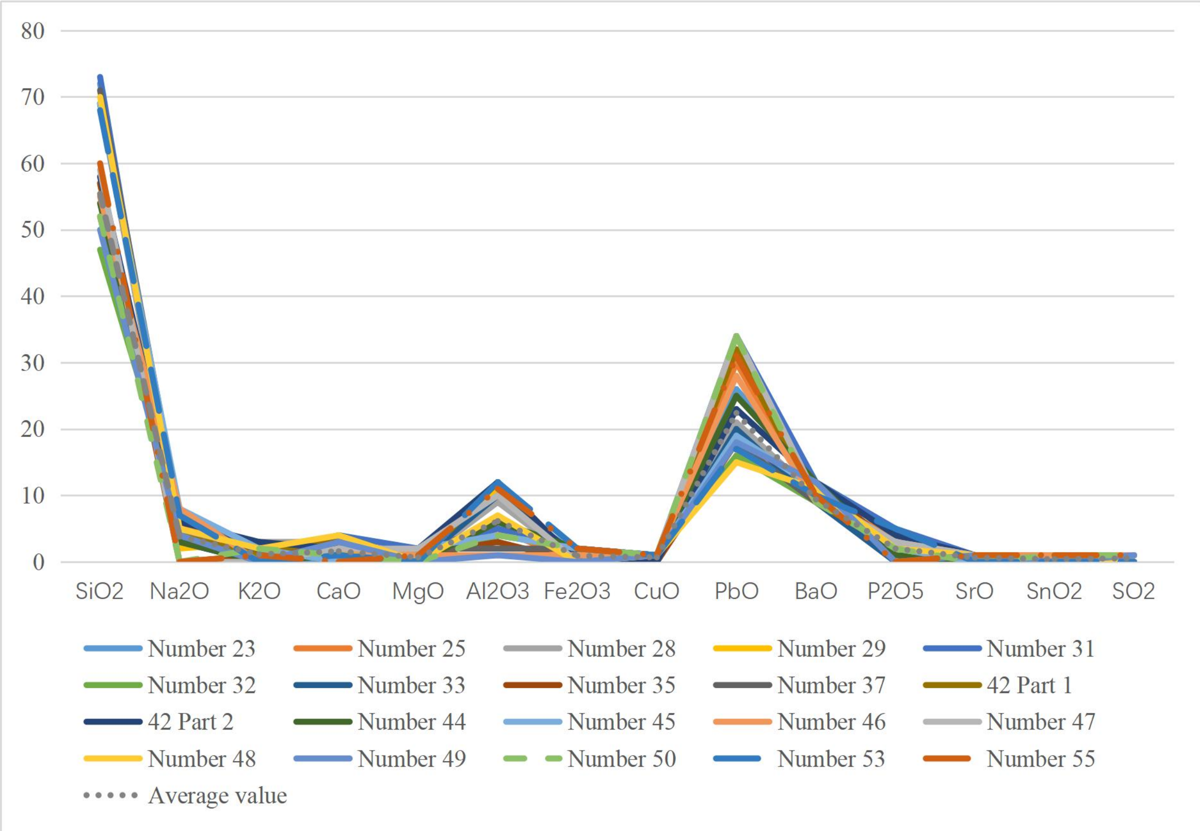

Figure 4 Lead barium glass fitting curve 3

4.3 Solution of the data classification model

Compare the sampling data of 7 sets of cultural relics. The category classified by the unknown cultural relic is the one with the smallest Euclidean distance from its sampling point data. The most appropriate category classification method filtered to derive the category attribution of heritage numbers in the systematic cluster analysis model, as shown in Table 9.

Table 9 Corresponding Categories

Cultural relic number	A1	A2	A3	A4	A5	A6	A7	A8
category	7	3	3	3	3	6	6	6

At the same time, it is necessary to test the classification using sensitivity as the testing standard and analyze and explore the range of errors generated. Obtain comparative images of eight fitted curves through the linear fitting. As shown in Figures 5 to 12:

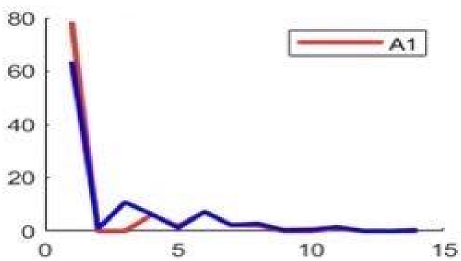

Figure 5 A1 and SiO_2-CaO-Al_2O_3

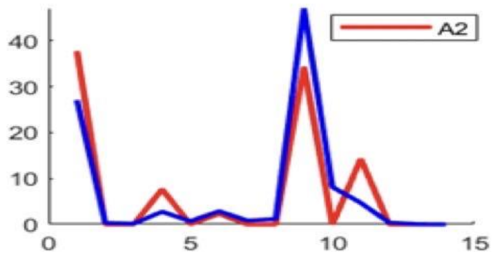

Figure 6 A2 and low BaO-high PbO-SiO_2

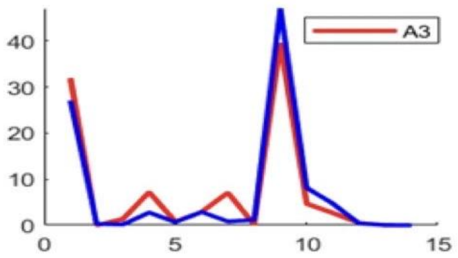

Figure 7 A3 and low BaO- high PbO-SiO_2

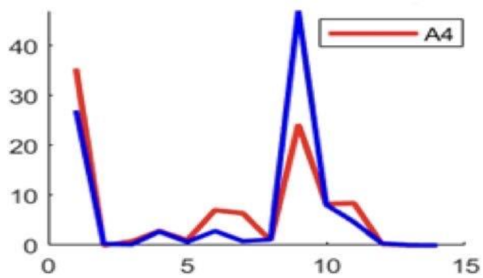

Figure 8 A4 and low BaO-high PbO-SiO_2

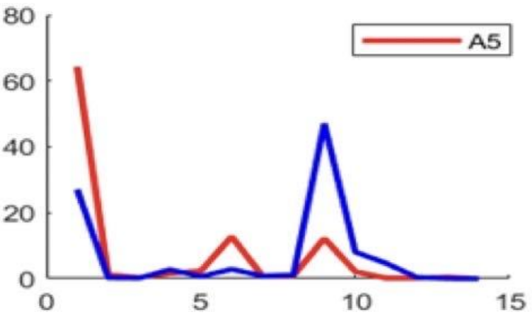

Figure 9 A5 and low BaO-high PbO-SiO_2

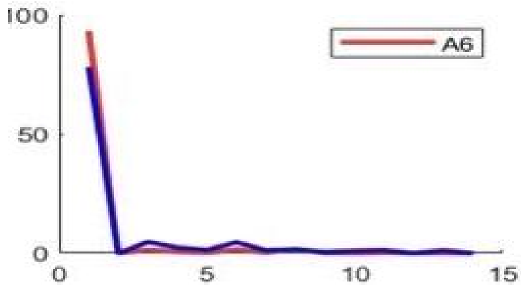

Figure 10 A6 and low SiO_2

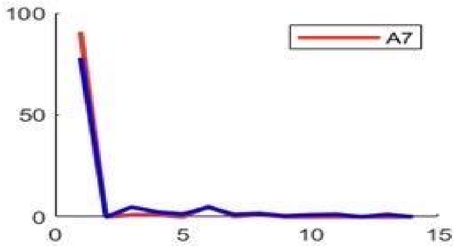

Figure 11 A7 and low SiO_2

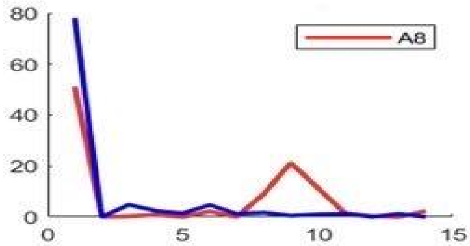

Figure 12 A8 and low SiO_2

The analysis of fitting Figure 5-12 shows that the proper curves of A2, A3, A1, A6, A7, and A8 are similar to the actual classification, with low sensitivity. The fitting images of A4 and A5 have poor similarity and high sensitivity.

5. Conclusion

(1) For lead barium glass, by comparing the changes in the content of various chemical elements before and after weathering, it is concluded that Na_2O and Al_2O_3 have a protective effect on weathered cultural relics. From never weathering to weathering, SiO_2 content decreases, while PbO, BaO, P_2O_5, and CaO content increases.

(2) For high potassium glass, the content of Na2O remains unchanged before and after weathering, while the range of SrO, SnO, and SO2 is almost zero. Before and after weathering, the content of SiO2 increases while the content of other elements decreases.

(3) The model used in the article transforms the known information description into good mathematical language and explores the relationship between the attributes of glass artifacts and weathering through the evaluation method of the model in a weighted manner. At the same time, further, explore its inherent regularity through fitting curves.

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