Analysis and identification of ancient glass based on correlation analysis

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Abstract: This paper focuses on the analysis and identification of ancient glass components. The correlation analysis of weathered or unweathered glass surface with glass type, decoration and color was conducted using spss software, and further analyzed by chi-square test, which concluded that weathered surface showed negative correlation with glass type. The glass was also classified one by one to study the statistical pattern of the chemical composition with and without weathering, and using factor analysis, the weight of each chemical composition was derived, and then the content of the composition before weathering was predicted.

Keywords: Ancient glass component content; Correlation analysis; Factor analysis method; SPSS; Weight prediction.

1. Introduction

Glass is a scarce item in the cultural exchange between China and the West in ancient times. After absorbing the glass-making technology from the West, China began to make its own glass, which is somewhat similar in appearance, but somewhat different in chemical composition.

In modern times, the main raw material of glass is quartz sand, the main component of which is silica, while some fluxes are added during the production process to reduce the melting speed. According to the different fluxes added, the type and characteristics of the final glass formed will also be different, for example, adding lead ore will eventually form lead-barium glass, adding substances containing high potassium elements can be used as fluxes, while forming potassium glass. Moreover, ancient glass preserved in modern times is susceptible to weathering by environmental and other factors, resulting in chemical reactions between elements inside the glass and the environment leading to changes in the internal chemical composition of the glass, so the proportion of components contained in the glass will also change, which in turn affects people's judgment of the category to which it belongs. Some artifacts are partially weathered but some distinctive features such as color and ornamentation can be seen.

The mathematical model is based on the official form 1 of the 2022 Mathematical Modeling C problem. Correlation analysis based on the relationship between whether the glass surface is weathered or not and its glass type, decoration and color [1-2]; and then statistical analysis of the chemical composition of the glass artifact surface with and without weathering using SPSS [3-4] software in combination with the type of glass. Finally, the annex given on the official website of the competition based on the test data of different weathering points of the artifacts in Table 2 to predict their chemical composition content before weathering.

2. Problem Analysis and Model Construction

In this study, the correlation between surface weathering and glass type, decoration, and color was first analyzed [5], and the significance results were obtained. A chi-square test was performed [6-7], and then the weights of the indicators were derived according to the factorial molecular method, and the chemical composition content before weathering was "reduced".

2.1 Ask a question

2.1.1 The degree of weathering of artifacts and the type of ornamentation

According to the data observation, the surface weathering of the artifacts with 34 pieces about 60%, while the surface of the artifacts without weathering 24 pieces accounted for 40%, it can be seen that the number of weathered artifacts and unweathered artifacts have a certain gap. Then according to the premise of weathering and unweathered analysis of the relationship between weathering and data on the type of decoration

Through data can be found: 1 weathering case, the number of class C has the most 17 pieces, followed by class A, the least class B. 2 no weathering case, A, C two types of the number of difference is not large. Comparing the two categories of weathered and for weathering, it can be seen that all of category B are weathered.

2.1.2 Weathering and color

The exterior color of glass artifacts allows visualization of whether the artifacts are weathered and what kind of glass they belong to. The color and weathering of which is shown in Figure 1. through Figure 1 can be seen:

1) The most significant weathering is blue-green and light blue glass artifacts, of which there is also a characteristic black.
2) No weathering of glass artifacts mainly blue-green and light blue. Comparison of weathering and no weathering can be found weathering is characteristic of black, judging weathering and no weathering only according to the blue-green and light blue and other colors to distinguish a certain degree of difficulty, but also should be combined with other methods to determine.

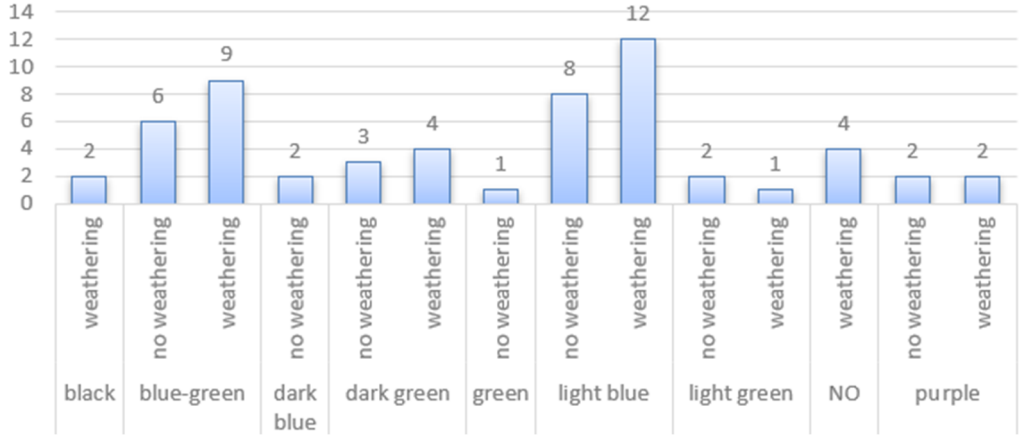


Figure 1. Weathering and color

2.1.3 Weathering and glass types

Through common sense, it is known that the degree of weathering difficulty of different types of glass will vary, so you can know roughly whether this glass artifact is easy to weather according to the type of glass, but it is not accurate enough, and there are other conditions to determine the specific combination. One of the proportional diagrams of glass type and whether it is weathered in Annex I is shown in Figure 2. It can be found in Figure 2 that the number of high potassium glass and lead-barium glass in the case of no weathering accounts for approximately the same proportion, while lead-barium glass accounts for most of the glass in the case of weathering while high potassium glass accounts for only a small proportion, so it can be seen that lead-barium glass is easily weathered, which may be related to the chemical composition of lead-barium glass.

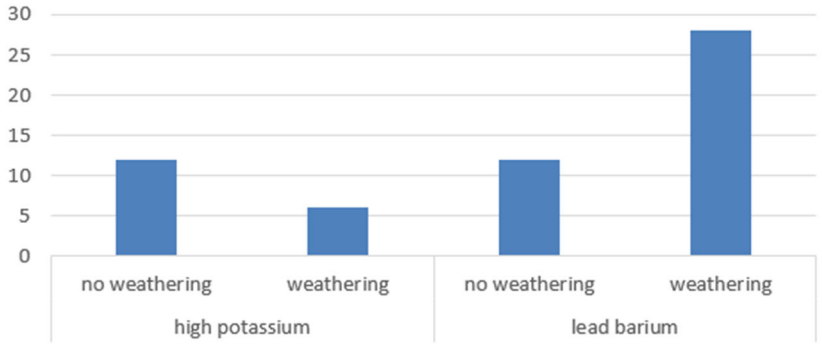


Figure 2. Weathering and glass types

2.2 Analysis and solution of the problem

The problem requires the solution of three subproblems, one of which is the analysis of surface weathering in relation to glass type, decoration and color for analysis; the second is the correlation analysis based on the data, using Spearman's correlation coefficient [8-9] to derive the relationship between surface weathering and these three indicators. The third is to predict the content of the pre-weathering chemicals based on the weathering data.

2.3 Data Processing

According to the results of the above analysis, the cumulative sum of the component ratios is not 100% due to the huge amount of data and the detection means, so the data with a cumulative sum between 85% - to 105% are considered as valid data. Therefore, the data were processed first, and it was possible that the cumulative sums of the 15th and 17th artifact detection points were outside the valid range. So these two data can be excluded.

2.4 Glass weathering model construction

Figure 3 shows a line graph of glass types and colors as well as the number of types, as can be seen:

1) For weathered artifacts, the highest total number of 17 is in category C, followed by category A and the least in category B. The most predominant weathering is blue-green and light blue glass artifacts, which also have a characteristic black color. Lead-barium glass accounts for the vast majority while high-potassium glass accounts for only a small percentage.
2) For the unweathered artifacts, there is little difference in the number of A, C, and the unweathered glass artifacts are also mainly blue-green and light blue, and the number of high-potassium glass and lead-barium glass account for roughly the same proportion.
3) In general, it can be found that all of Class B are weathered, and it is not easy to determine whether they are weathered artifacts based on color alone. At the same time, most of the weathered ones are found to be lead-barium glass, and most of the high potassium class glass is unweathered, so it can be seen at first glance that weathering is related to the type of glass.

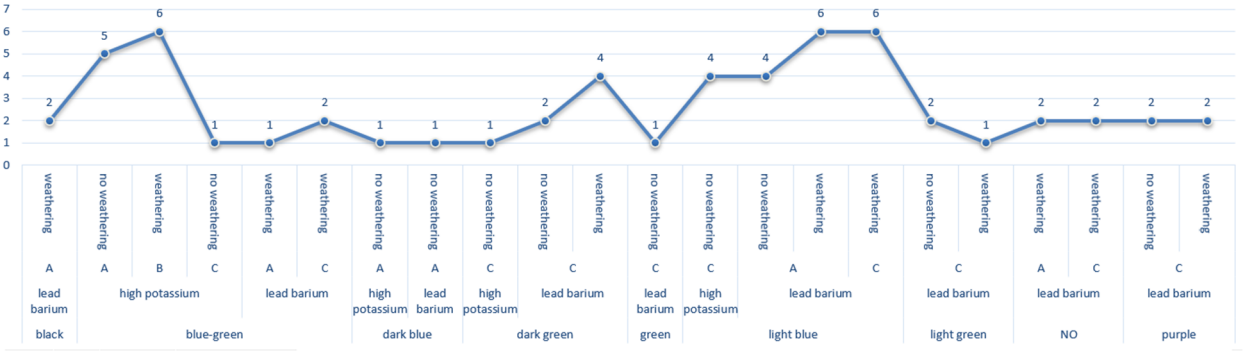


Figure 3. Integrated data

For the above data observation, it is possible to correlate the three characteristics of ornament, type and color with surface weathering, and the Spearman correlation analysis results of surface weathering and Ornament, type and color are 0.037,0.344,0.07 respectively. Taken together, the above analysis leads to the following conclusions.

1) The correlation coefficient values were 0.037, all of which were close to 0, and the p-values were all greater than 0.05, implying that there was no correlation between ornamentation and surface weathering.
2) All of the correlation coefficients between type and surface weathering coefficients showed significant values of -0.344, respectively, and the correlation coefficient values were less than 0, implying a negative correlation between type and surface weathering coefficients.
3) None of the correlation coefficients between color and surface weathering coefficient 1 will show significance, the correlation coefficient values are 0.070 respectively, all are close to 0, and all p-values are greater than 0.05, implying that there is no correlation between color and surface weathering coefficient 1.

2.5 Model Testing

Through the above analysis it is concluded that the surface weathering is mainly negatively correlated with the type, while then the significance test This paper mainly uses the chi-square test, where the main results are as follows Table 1.

Table 1. Cardinality test table

topic	name	surface weathering		total	x^2	p
		no weathering	weathering			
Ornament	A	45.83%	32.35%	37.93%	4.957	0.084
	B	0.00%	17.65%	10.34%		
	C	54.17%	50.00%	51.72%		
total		24	34	58		
color	light green	8.33%	3.33%	5.56%	6.287	0.507
	light blue	33.33%	40.00%	37.04%		
	dark green	12.50%	13.33%	12.96%		
	dark blue	8.33%	0.00%	3.70%		
	purple	8.33%	6.67%	7.41%		
	green	4.17%	0.00%	1.85%		
	blue-green	25.00%	30.00%	27.78%		
	black	0.00%	6.67%	3.70%		
total		24	30	54		
	lead barium	50.00%	82.35%	68.97%	6.880	0.009**
	high potassium	50.00%	17.65%	31.03%		
total		24	34	58		

* p<0.05 ** p<0.01

From the results of the chi-square test in Table 1, it can be seen that: different surface weathering samples do not show significance (p>0.05) for glass ornamentation, and color, so different surface

weathering samples show consistency for glass ornamentation, and color, and there is no difference. However, the surface weathering samples showed significance for the type of glass artifacts ($p<0.05$), so different surface weathering samples showed differences for the type, and the surface weathering showed 0.01 level of significance for the type ($x^2=6.880$, $p=0.009<0.01$), and the difference by percentage comparison shows that the proportion of weathering selected lead barium 82.35%, which is significantly higher than that of no Weathering selected 50.00%. The percentage of high potassium selected by no weathering is 50.00%, which is significantly higher than the selection ratio of 17.65% for weathering.

In conclusion, it can be seen that the surface weathering samples do not show significant differences for the two items of ornamentation and color, while the surface weathering samples show significant differences for the item of type. This is consistent with the results of Spearman's correlation analysis, which indicates that the results are more realistic and reliable.

2.6 Analysis and solution of statistical laws

2.6.1 Analysis of weathering problems of high potassium glass

Since the question requires the analysis of the statistical law of the chemical content with and without weathering in combination with the type of glass, and the prediction of the chemical content before weathering. Since there are only two types of glass, high potassium glass and lead-barium glass, the two types and the presence or absence of weathering on the surface can be divided into four cases, and since there is only one type of non-weathered high potassium glass and too little data, the solution is ignored. Then there are three remaining which are divided into three cases. Since each glass has more chemical components and some compounds have less data, we consider using factor analysis to reduce the dimensionality and then the weight of each factor, which is most sufficient to derive the weight of the components before weathering based on the weight.

2.6.2 Weathering model solution for high potassium glass

Firstly, the data of high potassium glass weathering are screened out, and the factor analysis is carried out to reduce the dimension, and the public of each factor is obtained. According to the weathering data of high potassium glass, it is found that very few high potassium glass contain sodium oxide (Na_2O) and tin oxide (SnO_2), so these two compounds are eliminated to analyze the weathering of high potassium glass. After exclusion, factor analysis, KMO and Bartlett's test were performed and the results are shown in Table 2 below. From Table 2, we can see that: the KMO is 0.520, which is greater than 0.5, meeting the basic requirement of factor analysis with KMO value greater than 0.5, indicating that it is suitable for factor analysis. The factor analysis extracted a total of three factors with eigenroot values greater than 1. The explained variance of these three factors after rotation was 48.999%, 20.701%, and 14.914%, respectively, and the explained variance after rotation was 84.614% cumulatively. Finally, the weights of each indicator are derived, as shown in Table 3.

Table 2. KMO and Bartlett's test

KMO Value		**0.520**
Bartlett's Sphericity inspection	approximate chi-square	216.427
	df	66
	p	0.000

Note: * $p<0.05$ ** $p<0.01$.

Table 3. Linear combination coefficients and weighting results

Name	Factor 1	Factor 2	Factor 3	Overall score coefficient	Weight
Feature root (after rotation)	5.88	2.484	1.79		
Explanation of variance	49.00%	20.70%	14.91%		
Silicon Dioxide (SiO_2)	0.3689	0.0932	0.2483	0.2802	9.88%
Potassium oxide (K_2O)	0.2609	0.0078	0.347	0.2142	7.55%
Magnesium oxide (MgO)	0.0712	0.5068	0.2056	0.2015	7.10%
Iron oxide (Fe_2O_3)	0.0032	0.5524	0.2597	0.1827	6.44%
Copper oxide (CuO)	0.1154	0.1503	0.4995	0.1917	6.76%
Lead oxide (PbO)	0.3825	0.2259	0.0003	0.2768	9.76%
Aluminum oxide (Al_2O_3)	0.1312	0.4864	0.0669	0.2068	7.29%
Calcium oxide (CaO)	0.111	0.0554	0.6601	0.1942	6.84%
Phosphorus pentoxide (P_2O_5)	0.3816	0.1453	0.1267	0.2789	9.83%
Barium oxide (BaO)	0.3908	0.1946	0.0042	0.2747	9.68%
Strontium oxide (SrO)	0.396	0.085	0.0495	0.2588	9.12%
Sulfur dioxide (SO_2)	0.3827	0.2233	0.0022	0.2766	9.75%

Therefore, the proportion of each chemical component under the weathering conditions of high potassium glass is shown above, and the weights can be used to approximate the proportion of each compound. Similarly, for the data under the weathering of lead-barium glass, it can be found that the data of sodium oxide (NaO), sulfur dioxide (SO_2), and tin oxide (SnO_2) are very few, so the content of these three compounds can be considered to be discharged, and finally a factor analysis was conducted to obtain the weights of each compound as follows Table 4.

Table 4. Results of linear combination coefficients and weights of lead and barium

Name	Factor 1	Factor 2	Factor 3	Overall score coefficient	Weight
Feature root (after rotation)	2.794	2.407	2.080		
Explanation of variance	25.40%	21.88%	18.90%		
C_ Silicon Dioxide (SiO_2)	0.5319	0.1106	0.1806	0.2923	11.05%
C_ Potassium oxide (K_2O)	0.0720	0.3614	0.0454	0.1601	6.05%
C_ Calcium oxide (CaO)	0.4077	0.3020	0.0825	0.2799	10.58%
C_ Magnesium oxide (MgO)	0.2123	0.4427	0.2440	0.2975	11.25%
C_ Aluminum oxide (Al_2O_3)	0.0691	0.5059	0.0867	0.2185	8.26%
C_ Iron oxide (Fe_2O_3)	0.0279	0.4277	0.1440	0.1932	7.31%
C_ Copper oxide (CuO)	0.0899	0.1034	0.6089	0.2426	9.17%
C_ Lead oxide (PbO)	0.4342	0.2613	0.2770	0.3322	12.56%
C_ Barium oxide (BaO)	0.0001	0.0944	0.6466	0.2160	8.17%
C_ Phosphorus pentoxide (P_2O_5)	0.4136	0.1782	0.0073	0.2197	8.31%
C_ Strontium oxide (SrO)	0.3571	0.1066	0.0706	0.1924	7.28%

Therefore, the predicted compound content before weathering is shown in Table 5.

Table 5. Compound content of lead barium glass before weathering

Compound name	Content
Sodium oxide (Na_2O)	0%
Silicon Dioxide (SiO_2)	11.05%
Potassium oxide (K_2O)	6.05%
Magnesium oxide (MgO)	11.25%
Iron oxide (Fe_2O_3)	7.31%
Copper oxide (CuO)	9.17%
Lead oxide (PbO)	12.56%
Aluminum oxide (Al_2O_3)	8.26%
Calcium oxide (CaO)	10.58%
Phosphorus pentoxide (P_2O_5)	8.31%
Barium oxide (BaO)	8.17%
Strontium oxide (SrO)	7.28%
Sulfur dioxide (SO_2)	0%
Tin oxide (SnO_2)	0%

2.7 Problem Summary and Result Analysis

This paper first processed the data and then analyzed the relationship between surface weathering and glass type, decoration and color, and concluded that the correlation between surface weathering and these three characteristics was significant and negative only for glass type and surface weathering. The correlations were verified by chi-square test, and the correlations were found to be true and reliable.

Factor analysis was then performed to classify the chemical components[10] according to the different glass types to derive the weights *w*, and to approximate the pre-weathering content by deriving the percentage of each compound before weathering based on the sum of the weights equal to 1.

3. Suggestions for problems

1. The correlation of each chemical element with surface weathering can be further analyzed to make the statistical pattern of chemical composition with or without weathering more accurate.

2. More sophisticated and accurate models such as deep learning and neural networks can be used to predict the content of chemical components before weathering by correlation analysis of known chemical components of glass.

Acknowledgements

The authors gratefully acknowledge the financial support from xxx funds.

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