Analysis and identification of glass relics

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Abstract: To study the composition and identification of glass relics, the identification model is established using a regression model, statistical analysis, and a grey correlation matrix. Firstly, the chemical composition content of cultural relics before weathering is analyzed. Secondly, the classification of glass relics is obtained. Finally, the differences in the chemical composition of glass products are analyzed. The results show that: (1) there are more correlations among the chemical components in high potassium glass, and the correlation between potassium oxide, magnesium oxide, alumina, iron oxide, and copper oxide is closed. (2) Potassium oxide, magnesium oxide, alumina, and iron oxide in lead barium glass are more closely related to calcium oxide.

Keywords: Glass relics;Composition and identification;Regression model;Statistical analysis;Grey incidence matrix.

1. Introduction

Glass products are one of the earliest human-made materials. The earliest glass products can be traced back more than 2500 years ago in Western Asia. Although ancient Chinese glass products are similar to Western glass products in appearance, there are great differences in chemical composition. The research on the chemical composition system of ancient glass products is of great significance to the glass-making process and the source of glass.

The main raw material of glass is quartz sand (silica). Pure quartz sand has a high melting point. When making glass products, the ancients often added special flux to lower the melting temperature of quartz sand. The commonly used fluxes are plant ash, saltpeter, and lead ore. In addition, stabilizers such as limestone should be added. Glass products can be obtained by heating and melting these raw materials, molding, and cooling. The main chemical composition of the final glass products is different due to the different fluxes added. According to the different fluxes, ancient glass products can be divided into two categories. One is a lead glass system made of lead ore as flux, such as lead barium glass, which has a high content of lead oxide and barium oxide. The other is alkali silicate glass made of alkali metal element compound as flux.

In this paper, the mathematical models are used to analyze and identify the composition of glass relics, which guides the archaeological work of glass relics.

2. Prediction model of chemical composition content before weathering

2.1. The relationship between the surface weathering of glass relics and glass types, patterns, and colors

The Chi-square test was used to analyze the correlation between decoration, type, color, and surface weathering. By analyzing the B value and OR value, the relationship between the factors is obtained; For the factors with weak correlation, the relationship between them and surface weathering is analyzed by the control variable method. For the weak correlation factors, the relationship between them and surface weathering was analyzed by the control variable method.

Chi-square test analysis results are shown in Table 1-3 [5-7]. According to the results, the significant P values of ornamentation and color on surface weathering are 0.056 and 0.57, respectively, which are greater than 0.05. It is indicated that there is no significant difference between decoration,

color, and surface weathering. Therefore, the correlation between weathering and decoration as well as color is weak. However, the significance p-value of type to surface weathering is 0.02, less than 0.05, indicating a significant difference between type and surface weathering, that is, a strong correlation.

Table 1. Decoration and weathering

Ornamentation	weathering	No weathering
A	9	11
B	6	0
C	15	13

Table 2. Types and weathering

type	weathering	No weathering
High potassium glass	6	12
Lead barium glass	24	12

Table 3 color and weathering

colour	black	Blue green	green	Light blue	pale green	dark blue	dark green	purple
weathering	2	9	0	12	1	0	4	2
No weathering	0	6	1	8	2	2	3	2

The logistic regression model is used further to analyze the relationship between types and surface weathering. A binary logistic regression model is established by setting surface weathering as set as the dependent variable and glass type as the independent variable. Use Spss to solve, and the results are shown in Table 4.

Table 2 Classification logistic regression results

item	coefficient of regression	standard error	Wald	P value	Or value	Or value 95% confidence interval upper limit	lower limit
constant	0.32	0.918	0.122	0.727	1.378	0.228	8.321
Cultural relic number	0.014	0.023	0.374	0.541	1.014	0.969	1.062
Type-high potassium	-1.19	0.826	2.079	0.149	0304	0.06	1．534

* * * *, * * and * represent significant levels of 1%, 5% and 10% respectively.

Every time the variable increases by one unit (the classification level changes from 0 to 1), the probability of weathering and not weathering changes by (OR value-1)%. According to the results, the influence factor α1of high potassium glass on weathering is 0.304, and the influence factor α2of lead barium glass on weathering is 0.534. Therefore, high-potassium glass cultural relics are less prone to weathering (Table 4).

According to the chi-square test results, the correlation between ornamentation and color and surface weathering is not significant, and the significant P value is greater than 0.05, so through the logistic regression model，its relationship with surface weathering cannot be obtained. Therefore, the conventional control variable method is used to explore the relationship between ornamentation, color, and surface weathering.

(1) ornamentation and surface weathering

The glass relics has three different ornamentations, which are A, B, and C.Regardless of color, the relationship between different types of cultural relics, ornamentation, and surface weathering is analyzed. The number of weathered and unweathered cultural relics corresponding to different

ornamentations under high potassium is shown in Table.6. The weathering conditions of cultural relics corresponding to different ornamentation under lead and barium are shown in Table 7.

By analyzing the table data, it is found that all the ornamentation A and C in the high potassium glass are unweathered, and all the ornamentation B is weathered. No cultural relic is decorated with B in barium glass, and the weathered number of cultural relics decorated with A and C is greater than that of unweathered ones (Tables 5 and 6).

Table 5. High potassium ornamentation and weathering

type	Ornamentation	weathering	No weathering
High potassium	A	0	6
	B	6	0
	C	0	6

Table 6. Lead and barium ornamentation and weathering

type	Ornamentation	weathering	No weathering
Lead barium	A	9	5
	B	0	0
	C	15	7

(2) Color and Surface Weathering

The relationship between color and surface weathering is analyzed separately regardless of ornamentation and type. According to the attached data, these cultural relics are black, blue-green, green, light blue, light green, dark blue, dark green, and purple, with a total of 8 colors. See Table 8 and Table 9 for the weathering conditions corresponding to each color of cultural relics under different types.

It is shown that the number of weathered and unweathered blue-green cultural relics in high-potassium glass is the same, and all the blue, dark blue, and dark green cultural relics are weathered. The relationship between color and weathering in barium glass is not obvious. All black and blue-green cultural relics are weathered, while all green and dark blue cultural relics are not weathered (Table 7,8).

Table 7. Color and weathering of high potassium

colour	black	Blue green	green	Light blue	pale green	dark blue	dark green	purple
weathering	0	6	0	0	0	0	0	0
No weathering	0	6	0	4	0	1	1	0

Table 8. Color and Weathering of Lead and Barium

colour	black	Blue green	green	Light blue	pale green	dark blue	dark green	purple
weathering	2	3	0	12	1	0	4	2
No weathering	0	6	1	4	2	1	2	2

2.2. Statistical law of chemical composition content of two types of glass with and without weathering.

Excel is used to average the chemical composition content, and the data is visually analyzed to obtain the chemical composition content laws of different types of glass cultural relics with and without weathering.

According to surface weathering, the data of high-potassium glass can be divided into two categories: weathered and unweathered. Under each category, the average value of each chemical component is calculated, and figure 1 is obtained by data visualization.

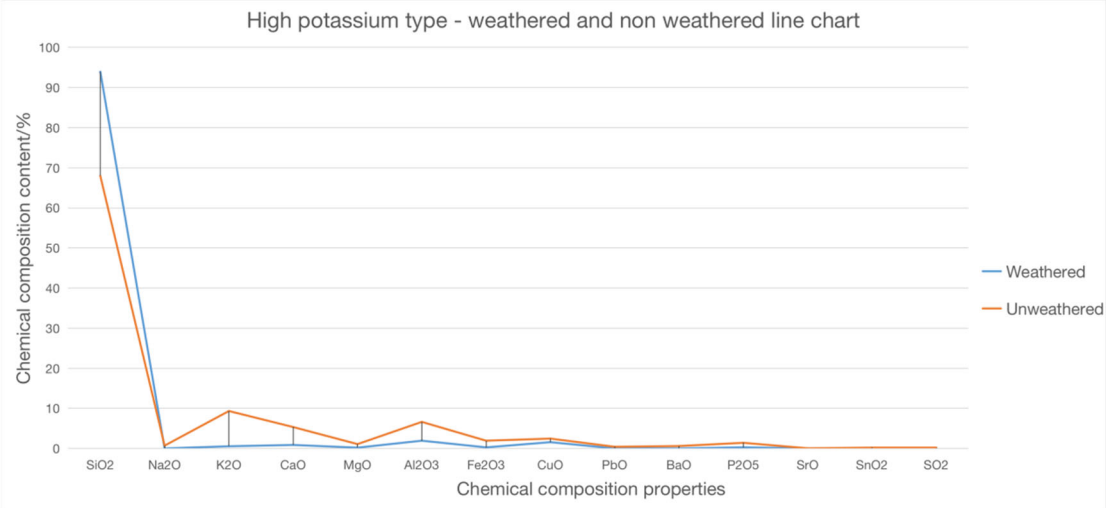


Fig. 1 Whether there is weathering chemical composition on the surface of high potassium glass.

When the surface of high-potassium glass cultural relics is weathered or unweathered, the silica content of 14 chemicals is the highest, and the silica content of weathered cultural relics is higher than that of unweathered cultural relics. In addition, compared with weathered cultural relics, the contents of potassium oxide, calcium oxide, aluminum oxide, iron oxide, and phosphorus pentoxide in unweathered cultural relics are all higher (Figure 1).

The data on lead-barium glass can also be divided into weathered and unweathered categories. Do the same operation with high potassium glass, and the data visualization results are shown in Figure 2.

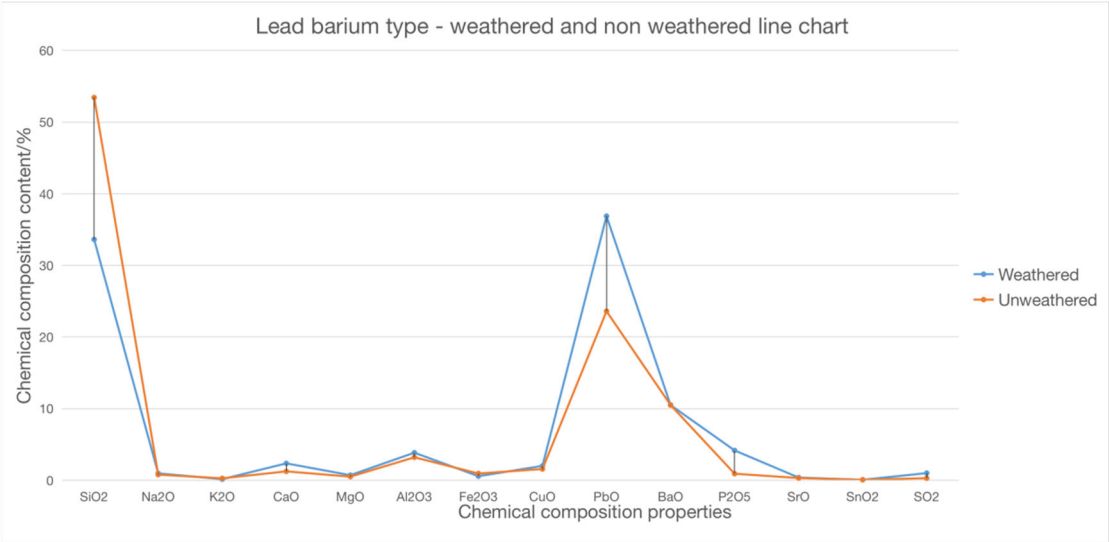


Fig. 2 Whether there is weathering chemical composition on the surface of the lead-barium glass

The content of silica in the unweathered barium glass cultural relics is the highest, followed by the content of lead oxide, and the contents of the remaining 12 chemical components are all at a low level. During weathering, the content of silica decreased, but the contents of calcium oxide, phosphorus pentoxide, and sulfur dioxide all increased, among which the content of lead oxide increased the most, exceeding the content of silica (Figure 2).

2.3. Predict the chemical composition before weathering.

The grey incidence matrix is usually used to analyze the degree of incidence between vectors or matrices. Firstly, the grey correlation matrix is established to study the quantitative relationship between surface weathering and ornamentation, type, and color.

Define whether the reference series is weathered or not:

$$x_j = \left(x_j(1); x_j(2); x_j(3), \ldots\ldots x_j(67)\right) \cdot j = 0 \quad (1)$$

Set the comparison series to each chemical composition series:

$$x_i = \left(x_j(1); x_j(2); x_j(3), \ldots\ldots x_j(67)\right) \cdot i = 1,2, \ldots.14 \quad (2)$$

From the above two series, the incidence matrix is defined as follows:

$$\xi_{ji}(k) = \frac{minmin\left|x_j(k) - x_i(k)\right| + \rho maxmax\left|x_j(k) - x_i(k)\right|}{\left|x_j(k) - x_i(k)\right| + \rho maxmax\left|x_j(k) - x_i(k)\right|} \quad (3)$$

Series correlation:

$$z^{(1)}(k) = \frac{x^{(1)}(k) + x^{(1)}(k-1)}{2}, k = 2,3,4 \quad (4)$$

As ζji(k) can only reflect the correlation between points, define the grey correlation degree:

$$r_{ij} = \frac{\sum_{k=1}^{n} \zeta_{ji}(k)}{n}, k = 2,3,4 \quad (5)$$

Write the correlation between xi and xj in matrix form to get the grey correlation matrix. Using Matlab to solve the model, the correlation degree of high potassium, lead, and barium to each chemical component was obtained.

It is assumed that the chemical composition content of weathered cultural relics is xi, and that of each chemical component before weathering is x'i.Combining the above three variables extracted from the two models, the weathering reduction model is established as follows:

$$x_i + \alpha \cdot \beta_i \cdot \Delta x_i = x_i' \quad (6)$$

The prediction results of weathering points of high potassium glass relics are shown in Table 8, and those of lead barium glass relics are shown in Table 9

Table 8. prediction results of weathering point of high potassium glass

Sampling point	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
07	93.22	0.14	0.20	0.97	0.02	1.87	0.13	3.21	0.01	0.012	0.59	0.0008	0.0041	0.002
09	95.61	0.14	0.39	0.52	0.02	1.21	0.28	1.53	0.01	0.012	0.33	0.0008	0.0041	0.002
10	97.36	0.14	0.72	0.11	0.02	0.70	0.22	0.81	0.01	0.012	0.02	0.0008	0.0041	0.002
12	94.88	0.14	0.81	0.62	0.02	1.35	0.25	1.63	0.01	0.012	0.13	0.0008	0.0041	0.002
22	92.94	0.14	0.54	1.56	0.62	3.39	0.31	0.53	0.01	0.012	0.19	0.0008	0.0041	0.002
27	93.31	0.14	0.19	0.84	0.52	2.40	0.16	1.52	0.01	0.012	0.33	0.0008	0.0041	0.002

Table 9. prediction results of lead barium glass weathering point

Sampling point	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
08	4.61	0	0	3.19	0	1.11	0	3.14	32.45	30.62	7.56	0.53	0	15.03
09	53.79	7.92	0	0.50	0.71	1.42	0	2.99	16.98	11.86	0	0.33	0	0
10	3.72	0	0.4	3.01	0	1.18	0	3.6	29.92	35.45	6.04	0.62	0	15.95
12	17.11	0	0	0	1.11	3.65	0	1.34	58.46	0	14.13	1.12	0	0
22	60.74	3.06	0.2	2.14	0	12.69	0.77	0.43	13.61	5.22	0	0.26	0	0
27	54.61	0.3	2.08	1.2	6.5	1.27	0.45	23.02	0.01	4.19	4.32	0.3	0	0

3. Classification of glass relics

3.1. Integrated classification model of decision tree algorithm

In order to further improve the classification accuracy of the gradient lifting decision tree algorithm, we consider adding the regular term to improve the algorithm, to establish the improved gradient lifting decision tree algorithm model. The regular term is a function reflecting the complexity of the decision tree, and adding a common term can reduce the complexity of the decision tree algorithm [8-11].

The data set is divided into 0.3 test sets and 0.7 training sets. When the number of base classifiers is 100, the model integrates 100 decision trees (table 10).

Table 10 model parameters

Parameter name	Parameter value
Training time	0.003s
Data segmentation	0.7
data shuffle	no
Cross-validation	no
Number of base classifiers	100
Learning rate	1

The evaluation results of the model are shown in Table 11. Quantitative indicators measure the prediction effect of AdaBoost.Among them, through the evaluation index of the cross-validation set, the super parameters can be adjusted continuously to obtain a reliable and stable model.

Table 11 model evaluation results

	Accuracy	recall	Accuracy	F_1
Training set	1	1	1	1
Test set	1	1	1	1

The results of the cultural relics classification are shown in Table 12. The accuracy of the model results is 100%, and the sum of error squares SSE is 0, so the model is reasonable.

Table 12 Classification forecast results

Prediction result	Probability _ lead dam	Probability _ lead dam	P_2O_5	CaO	NaO	SiO_2	MgO	Al_2O_3	Fe_2O_3	K_2O	SnO	CuO	BaO	SO_2
High potassium	2.2204×10^{-16}	0.9998	1.06	6.08	0	78.45	1.86	7.23	2.15	0	0	2.11	0	0.51
Qianba	0.9998	2.2204×10^{-16}	14.27	7.63	0	37.75	0	2.33	0	0	0	0	0	0
Qianba	0.9998	2.2204×10^{-16}	2.68	7.19	0	31.95	0.81	2.93	7.06	1.36	0	0.21	4.69	0
Qianba	0.9998	2.2204×10^{-16}	8.45	2.89	0	35.47	1.05	7.07	6.45	0.79	0	0.96	8.31	0
Qianba	0.9998	2.2204×10^{-16}	0.19	1.64	1.2	64.29	2.34	12.75	0.81	0.37	0.49	0.94	2.16	0

High potassium	2.2204×10^{-16}	0.9998	0.21	0.64	0	93.17	0.21	1.52	0.27	1.35	0	1.73	0	0
High potassium	2.2204×10^{-16}	0.9998	0.13	1.12	0	90.38	0	5.06	0.24	0.98	0	1.17	0	0.11
Qianba	0.9998	2.2204×10^{-16}	1.46	0.89	0	51.12	0.01	2.12	0.01	0.23	0.01	9.01	11.34	2.26

3.2. Sensitivity test of classification results [12]

Five data perturbations verified the sensitivity of the classification results on the samples, and the perturbation results are shown in Table 13 below. The prediction results obtained by five disturbances are the same as the initial classification results, indicating that the classification results have low sensitivity and good stability.

Table 13 Disturbance results

	1% disturbance	2% disturbance	5% disturbance	10% disturbance	20% disturbance	50% disturbance
Prediction result _Y	Prediction result _Y	Prediction result _Y	Prediction result _Y	Prediction result _Y	Prediction result _Y	Prediction result _Y
High potassium	High potassium	High potassium	High potassium	High potassium	High potassium	High potassium
Lead barium	Lead barium	Lead barium	Lead barium	Lead barium	Lead barium	Lead barium
Lead barium	Lead barium	Lead barium	Lead barium	Lead barium	Lead barium	Lead barium
Lead barium	Lead barium	Lead barium	Lead barium	Lead barium	Lead barium	Lead barium
Lead barium	Lead barium	Lead barium	Lead barium	Lead barium	Lead barium	Lead barium
High potassium	High potassium	High potassium	High potassium	High potassium	High potassium	High potassium
High potassium	High potassium	High potassium	High potassium	High potassium	High potassium	High potassium
Lead barium	Lead barium	Lead barium	Lead barium	Lead barium	Lead barium	Lead barium

4. Differences in the chemical composition of glass products

Firstly, cultural relics are classified into various categories according to different criteria: according to weathering conditions, they can be divided into weathered and unweathered; according to the type of glass, they can be divided into high potassium glass and lead barium glass. Secondly, the association rule model based on the Apriori algorithm is established, the relationship between the chemical components of different categories of cultural relics under the two classification systems is analyzed, and the association rules are extracted. Finally, the differences in association rules between different categories under each classification system are analyzed.

4.1. Association rule model based on Apriori algorithm [13-15]

This paper uses the confidence degree to analyze the relationship between components. When the confidence degree is 1, the probability of the conclusion is high when the precondition appears.

There are 8 association rules among weathered cultural relics among their chemical compositions (Table 14).

Table 14 Association Rules with Strong Association in Weathered Cultural Relics

precondition	conclusion	Confidence level
MgO, Fe_2O_3, PbO, P_2O_5	CaO	1
CaO、MgO、Fe_2O_3、P_2O_5	PaO	1
UgO, Fe_2O_3，PbO, SrO	CaO	1
CaO, Fe_2O_3, PbO, SrO	MgO	1
CaO, MgO, Fe_2O_3, SrO	PaO	1
Fe_2O_3, PbO, SrO	CaO, MgO	1
MgO, Fe_2O_3, SrO	CaO, PaO	1
CaO, Fe_2O_3, SrO	MgO, PaO	1
Fe_2O_3, SrO	MgO, PaO, CaO	1

There are 16 association rules among unweathered cultural relics' chemical compositions (Table 15).

Table 15 Association rules with strong association in unweathered cultural relics

precondition	conclusion	Confidence level
MgO, Fe_2O_3, PbO, P_2O_5	CaO	1
Ca O、Mg O、Fe_2O_3, P_2O_5	PaO	1
Ug O, Fe_2O_3，Pb O, Sr O	CaO	1
Ca O, Fe_2O_3, Pb O, Sr O	MgO	1
Ca O, Mg O, Fe_2O_3, Sr O	PaO	1
Fe_2O_3, Pb O, Sr O	CaO, MgO	1
Mg O, Fe_2O_3, Sr O	CaO, PaO	1
Ca O, Fe_2O_3, Sr O	MgO, PaO	1
Fe_2O_3,Sr O	MgO, PaO, CaO	1

For cultural relics with high potassium content, there are 11 association rules among their chemical compositions (Table 16).

Table 16 Association Rules with Strong Association in High Potassium Cultural Relics

precondition	conclusion	Confidence level
K_2O, Ca O, Mg O, Cu O	Fe_2O_3	1
K_2O, Ca O, Mg O, Fe_2O_3	CuO	1
K_2O, Ca O, Mg O	Fe_2O_3，CuO	1
K_2O, Ca O, Al_2O_3, Cu O	Fe_2O_3	1
K_2O, Ca O, Al_2O_3, Fe_2O_3	CuO	1
K_2O, MgO, Al_2O_3, CuO	Fe_2O_3	1
K_2O, MgO, Al_2O_3, Fe_2O_3	CuO	1
K_2O, MgO, Al_2O_3	Fe_2O_3，CuO	1
CaO, MgO, Al_2O_3，CuO	Fe_2O_3	1
CaO, MgO, Al_2O_3，Fe_2O_3	CuO	1
CaO, MgO, Al_2O_3	Fe_2O_3，CuO	1

There are five association rules among the chemical compositions of lead-barium cultural relics (Table 17).

Table 17 Association Rules with Strong Association in Lead-barium Cultural Relics

precondition	conclusion	Confidence level
K_2O, MgO, Al_2O_3, Fe_2O_3	CaO	1
MgO, Al_2O_3, PbO, P_2O_5	CaO	1
MgO, Fe2O3, PbO, SrO	CaO	1
CaO, MgO, Fe_2O_3, SrO	PbO	1
MgO, Fe_2O_3, SrO	PbO, CaO	1

4.2. Differences in chemical composition relationship among classes

Excel was used to study the differences in chemical compositions relationship between weathered and unweathered cultural relics and the differences in the chemical composition relationship between high-potassium and lead-barium cultural relics.

Differences in chemical composition relationship between weathered cultural relics and unweathered cultural relics are concluded as follows:

1. For unweathered glass, there are more connections and closer relationships among chemical components.

2. After weathering, the relationship between silica, potassium oxide, lead oxide, and other chemical components has significantly changed, indicating that weathering will affect the content of these components.

Differences between the chemical composition relationship of high potassium cultural relics and lead-barium cultural relics are as below:

1. The correlation between potassium oxide, magnesium oxide, aluminum oxide, iron oxide, and copper oxide in high potassium glass is closer, and that between potassium oxide, magnesium oxide, aluminum oxide, iron oxide, and calcium oxide in lead-barium glass is closer.

2. The chemical components in high potassium glass are more closely related.

5. Summary

(1) The model can predict the specific contents of 14 chemical components of the glass before weathering according to the detection data of weathering points.

(2) The model can analyze the chemical composition of unknown glass cultural relics and identify their glass types. The prediction results obtained after five data disturbances of different degrees are all the same as the initial classification results, which indicates that the classification results have low sensitivity and good stability.

(3) Weathering will affect the content of silicon dioxide, potassium oxide, and lead oxide, which will greatly change the relationship between these components and other chemical components.

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