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Chemical Analyses of Xiong-nu Pottery: A Preliminary Study of Exchange and Trade on the Inner Asian Steppes

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While there have been studies on the trade and exchange between the Han Empire and Xiong-nu confederacy, the nature of the movement of goods within the Xiong-nu confederacy has yet to be addressed. The purpose of this study is to provide a starting point to remedy this lacuna. Pottery from six sites was chemically characterized by energy dispersive X-ray fluorescence (EDXRF). Model-based clustering using the classification maximum-likelihood approach was used to find clusters in the principal component (PC) scores. The classification maximum-likelihood cluster analysis indicates that there are three spherical clusters of variable volume in the chemical data. The three clusters are interpreted as reflecting regional clay deposits. On the basis of the distribution patterns of the chemical groups, only a limited amount of pottery was moved across the territory controlled by Xiong-nu confederacy.

Keywords: ALTAI, CLASSIFICATION MAXIMUM-LIKELIHOOD, ENERGY-DISPERSIVE X-RAY FLUORESCENCE (EDXRF), MODEL-BASED CLUSTERING, PRINCIPAL COMPONENT SCORES, TRANS-BAIKAL, XIONG-NU.

Introduction

The term "Xiong-nu" is used both as a designation for an ethnic group and a confederation of nomadic and sedentary peoples who resided on the Inner Asian steppes from the 3rd century BC until the 2nd century AD (Barfield, 1989: 32–84; Ishjamts, 1994; Minyaev, 1985, 1995; Yü, 1990). In the late 3rd century BC, the original ethnic group began a series of conquests throughout Inner Asia, forcing the various nomadic and sedentary peoples residing there to pay them tribute and become part of their tribal confederacy. The Xiong-nu confederacy was brought to an end in the late 1st century AD, but the term Xiong-nu is used in the Chinese annals as late as the 5th century AD.

While Xiong-nu contacts with the Han Empire have been the focus of several art historical studies (see for example Trever, 1932; Umehara, 1960), the nature of contacts within their confederacy has yet to be addressed. The purpose of this study is to provide a starting point to remedy this situation. As has been demonstrated in numerous other studies, chemical studies of ceramics are essential in defining both inter- and intra-regional contacts between contemporary settlements (see for example Bishop, Rands & Holley, 1982; Jones, 1986; King *et al*., 1986; Lizee, *et al*., 1995; Neff, Bishop & Arnold, 1986). Energy dispersive X-ray fluorescence (EDXRF) was used in this study to determine the minor and trace element chemistry of pottery sherds from six separate Xiong-nu sites. Principal component analysis and model-based clustering techniques were then used to identify compositional groups in the data set. Afterwards, the relationship between the compositional groups and site location was examined.

Sites and archaeological materials

The pottery analysed in this study came from both settlements and cemeteries dating to the Xiong-nu period (circa 2nd century BC to 2nd century AD). The locations of these sites are shown in Figure 1. Derstui is a Xiong-nu settlement and cemetery located in the

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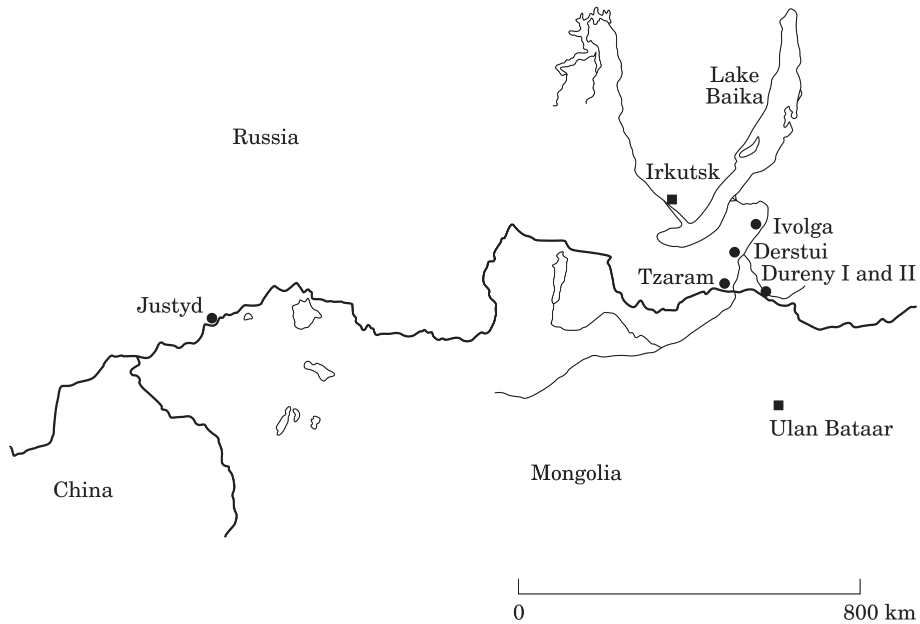

Figure 1. Map of the archaeological sites mentioned in the text.

Selenge River drainage basin (Minyaev, 1998*a*). Twenty-one of the pottery samples came from Dureny I, a settlement that extended 11 km along the Chikoy River (Minyaev, 1988). Dureny II, approximately 1·5 km from Dureny I on the opposite bank of the Chikoy River, is a multi-period site, containing cultural layers pre- and post-dating the Xiong-nu confederacy (Minyaev, 1988). Three different houses and five different burials yielded the samples from Ivolga (Davydova, 1995, 1996). Seven pottery samples came from three burials in the Tzaram cemetery. Due to the size and shape of the burial mounds, Tzaram is believed to be a cemetery for the Xiong-nu elite, or possibly even a *shan-yu* (Minyaev, 1998*b*, 2000). Twenty-three samples came from the Justyd settlement site in the Altai (Kubarev & Zhuravleva, 1986).

The Xiong-nu pottery examined in this study can be divided into two broad ware types. One ware type is typically grey or greyish-brown in colour and is characterized by a series of fairly standard sizes, shapes, and incised decorations. They were hand-constructed by coiling and often finished on a wheel. They were not painted or slipped. The second ware type is a coarse, reddish earthenware characterized by vertical rims and no decorations. While the two wares are found in the same stratigraphic levels at the sites in this study, it is uncertain whether they represent pottery made by two distinct ethnic groups, or have different functions, or represent specialist versus non-specialist production. For more details on Xiong-nu pottery, the reader is referred to Minyaev (1998*a*).

It is uncertain how pottery was manufactured during the Xiong-nu period in Inner Asia. While metalworking facilities have been found at such Xiong-nu sites as Ivolga (see Figure 1), pottery wasters and structures that can be definitively identified, as pottery kilns have not been found. The favoured hypothesis is that pottery production was done at the household level using local clays and tempers (Minyaev, 1998*a*).

Analytical Methodology

The minor and trace element composition of the pottery examined in this study was determined using energy dispersive X-ray fluorescence (EDXRF). The elemental analyses were performed at the National Museum of Japanese History using a Philips PV9550 EDXRF machine equipped with a rhodium X-ray tube, an aluminum filter and an EDAX DX4 X-ray analyser. The X-ray tube was operated at 30 kV, 0·30 milliamps in air at 250 s livetime to generate X-ray intensity data for the elements iron (Fe), lead (Pb), manganese (Mn), rubidium (Rb), strontium (Sr), thorium (Th), titanium (Ti), yttrium (Y), zinc (Zn), and zirconium (Zr). The X-ray beam size was approximately 0·75 cm in diameter. The K_{α} and L_{α} X-ray intensity line data was converted to concentration values using a Compton scatter matrix correction and the linear regression of a set of Geological Survey of Japan (GSJ) mineral standards, and National Institute of Standards and Technology (NIST) glass standards. Inter-element effects are accounted for by using a Lucas-Tooth and Price correction. The detection limits, as determined on geological standards, are listed in the Appendix.

To monitor the operation of the EDXRF unit, standards of known composition were run with the unknowns. These results are also contained in the Appendix. The analytical accuracy and precision, as defined by Bishop *et al*. (1990), for most trace elements is 20% or less.

Irradiation was done on a polished cross-section of each sherd. The final surface finish was 600 microns or finer. After polishing, each sherd was ultrasonically cleaned in distilled, de-ionized water for 15 min and dried at 35°C for 48 h.

Mathematical Methodology

The raw data was base 10 log-transformed to compensate for the differences in magnitude between the minor and trace elements. For cases below the detection limit, one half the detection limit was used in the log transformation.

Principal components analysis (PCA) was calculated on the log-transformed chemical data. This is a commonly utilized technique in compositional studies of ceramics since it is a way of reducing the dimensionality of the data and accounting for correlations between the variables (Baxter, 1994; Bishop & Neff, 1989; Lizee *et al*., 1995). It should also be noted that many model-based clustering methods perform best on low dimensional data (Fraley & Raftery, 2000; Toscano & Marriott, 1999); calculating PC scores is one way of reducing the dimensionality.

Model-based cluster analysis was used to determine the number of groups in the PCA scores. While the term "model-based cluster analysis" encompasses a range of methods, it is often assumed that the data are a mixture of multivariate normal clusters; the size, shape and orientation of the clusters can be specified by the user or tested for.* The model-based cluster analysis methodology used here has also been called the *classification maximum-likelihood* approach. Mathematical treatments of model-based clustering utilizing the classification maximum-likelihood approach can be found in Banfield & Raftery (1993); Fraley (1998); Fraley & Raftery (1998*b*, 2000), and Papageorgiou *et al*. (2000).

In the classification maximum-likelihood approach, the initial groups are either specified by the user or by a hierarchical, agglomerative clustering method in model-based clustering. The EM algorithm is then used to re-allocate cases to satisfy the particular model (see below). Re-allocation is done to maximize the conditional probability that a given case belongs to its assigned group for the given number of groups. The Bayesian Information Criterion (BIC), a type of Bayes Factor, is calculated for all possible group configurations to determine which clustering model(s) and the number of groups that are valid (Kass & Raftery, 1995; Fraley & Raftery, 2000). The higher the BIC value, the stronger the evidence for the model.* In comparing models, a difference of 2–6 is positive evidence, from 6–10 is strong evidence, and greater than 10 is considered very strong evidence (Kass & Raftery, 1995).

All model-based clustering in this paper is done using the MCLUST software package for R (Fraley, 1999). The MCLUST program fits multivariate normal models according to the eigenvalue decomposition of the covariance matrix as developed by Banfield & Raftery (1993). Multivariate normal models with the following conditions can be fit with MCLUST: (1) spherical distributions with equal volume and shape (EI); (2) spherical distributions with variable volume, but equal shape (VI); (3) ellipsoidal distributions with equal orientation, shape, and volume (EEE); (4) ellipsoidal distributions with variable volume, shape and orientation (VVV); (5) ellipsoidal distributions with equal shape and volume, but variable orientation (EEV); and (6) ellipsoidal distributions with variable volume and orientation, but fixed shape (VEV). The algorithms for the program have been published in Fraley (1998).†

Ward's method of cluster analysis fits a spherical distribution with equal volume and shape to the data (Banfield & Raftery, 1993; Fraley, 1998). Other methods of hierarchical cluster analysis, such as single linkage cluster analysis or average link cluster analysis that are commonly used in compositional studies, do not fit the data to any population distribution and have no known statistical model (Fraley & Raftery, 2000). One of the advantages of model-based clustering is that it can fit statistically based models to the data. Furthermore, as has been noted by a variety of authors (Slane *et al*., 1994; Papageorgiou *et al*., 2000), due to correlations between the elements, groups in compositional data often have an elongated or elliptical shape in multi-dimensional space. The advantage of using the classification maximum-likelihood approach as implemented by MCLUST is that it can fit elliptical distributions to the compositional data.

There are two other advantages of the classification maximum-likelihood approach. Simulation studies by Banfield & Raferty (1993) indicate that it performs well in discovering clusters that overlap or intersect in multidimensional space. The other advantage is that the BIC score provide a statistical basis for determining the number of groups. The more traditional ways of cluster analysis do not have a way of statistically assessing the number of clusters in the data set.

With these advantages in mind, it was decided to use the classification maximum-likelihood approach. While some may object to fitting multivariate normal

*In addition to the classification maximum-likelihood approach used here, there are a variety of Bayesian approaches (see Buck, 1993; Cheeseman & Stutz, 1996), and the mixture modeling approach (McLachlan & Basford, 1988; McLachlan & Peel, 1999).

*The definition of the BIC value is reversed in MCLUST; most other authors and programs want the BIC value minimized. The reasons for this can be found in Fraley & Raferty (1998*a*: 6).

†The version of MCLUST for the program R was used in this paper. There are slight differences between its implementation and output features in the R and S programs.

Table 1. Minor and trace element composition of the sherds; all values in parts per million (ppm)

Sample	Site	Ti	Mn	Fe	Zn	Th	Rb	Sr	Y	Zr
d:009	Derstui	11,298	1849	56,573	98	14	171	329	37	321
d:009a	Derstui	12,744	800	48,053	43	9	115	896	27	223
d:009b	Derstui	5376	nd	18,648	nd	nd	38	270	23	116
d:009c	Derstui	8342	836	59,232	103	13	151	304	45	341
d:010	Derstui	3944	1655	54,577	153	11	144	578	28	369
d:011	Derstui	8504	1405	47,993	97	11	161	350	26	285
d:011a	Derstui	5671	709	34,843	120	14	167	422	33	324
d:011b	Derstui	12,215	838	62,504	140	17	167	392	42	375
d:014a	Derstui	7036	513	34,304	226	10	162	363	31	396
d:014b	Derstui	4704	797	49,587	98	13	155	712	29	268
d:014c	Derstui	7023	1540	62,400	158	10	106	469	27	264
d:014d	Derstui	6272	1041	37,881	137	33	196	236	58	437
d1:001	Dureny I	12,540	910	41,316	116	8	93	491	34	217
d1:002	Dureny I	11,272	1422	44,506	131	14	164	340	37	383
d1:003	Dureny I	5892	726	35,065	672	nd	60	387	23	178
d1:004	Dureny I	10,397	1103	47,333	110	25	142	424	37	342
d1:005	Dureny I	7234	1387	38,819	106	12	81	417	20	195
d1:006	Dureny I	8343	1091	48,717	108	7	97	564	24	248
d1:007	Dureny I	4257	702	44,307	79	8	85	726	24	219
d1:008	Dureny I	5211	1223	49,189	112	13	104	494	29	232
d1:033	Dureny I	6481	1346	33,284	104	nd	106	312	23	200
d1:034	Dureny I	8457	1133	38,832	113	nd	84	399	25	216
d1:035	Dureny I	4478	791	36,464	78	nd	82	776	20	137
d1:036	Dureny I	7978	500	29,636	49	8	119	276	22	210
d1:037	Dureny I	5420	306	24,508	16	nd	51	411	25	134
d1:038	Dureny I	6170	548	34,950	77	12	125	385	23	200
d1:039	Dureny I	7802	1202	47,579	68	9	90	603	22	195
d1:040	Dureny I	6662	1246	44,673	85	nd	78	526	23	179
d1:041	Dureny I	6226	1426	54,759	122	8	106	405	34	329
d1:042	Dureny I	8148	643	23,989	88	7	52	254	13	114
d1:043	Dureny I	11,066	908	59,747	117	10	124	578	31	324
d1:044	Dureny I	8179	1456	53,374	106	15	131	336	31	332
d1:045	Dureny II	5455	718	35,574	64	13	145	399	29	224
d2:046	Dureny II	4629	455	37,639	28	25	192	193	37	257
d2:047	Dureny II	6862	1013	40,298	79	17	138	261	37	244
d2:048	Dureny II	9565	581	76,464	153	10	132	365	34	292
d2:049	Dureny II	11,821	671	75,937	126	9	118	396	31	316
d2:050	Dureny II	5348	892	31,859	141	14	147	222	32	254
d2:051	Dureny II	4500	873	36,608	94	20	194	170	45	348
d2:052	Dureny II	6695	839	43,006	72	9	121	289	28	266
d2:053	Dureny II	8680	1376	50,693	104	nd	97	413	33	303
iv:015	Ivolga	6558	683	21,038	75	nd	107	304	17	156
iv:016	Ivolga	6283	238	22,504	51	nd	80	299	26	159
iv:017	Ivolga	5396	nd	15,030	30	nd	38	268	18	54
iv:018	Ivolga	7226	1550	40,862	15	15	172	522	30	237
iv:019	Ivolga	7232	867	41,541	113	16	176	295	30	309
iv:020	Ivolga	5949	878	36,735	75	nd	72	342	20	181
iv:022	Ivolga	7693	675	37,158	89	10	88	445	24	136
iv:023	Ivolga	7428	1004	49,117	83	15	156	564	31	272
iv:024	Ivolga	5613	187	21,016	37	10	99	538	17	171
j:106	Justyd	10,048	1455	50,958	128	10	180	163	37	262
j:139	Justyd	5193	692	51,749	104	12	170	177	39	240
j:146	Justyd	6828	693	43,073	173	13	142	138	37	217
j:1475	Justyd	8445	785	54,554	170	19	151	120	49	299
j:1624	Justyd	2745	904	50,197	113	19	156	184	37	248
j:190	Justyd	4291	1380	30,232	27	nd	102	108	24	160
j:216	Justyd	8988	1370	60,698	129	23	148	211	39	247
j:3102	Justyd	5042	1454	50,246	183	13	168	116	48	265
j:316	Justyd	7553	681	50,187	118	15	166	182	34	232
j:3259	Justyd	9236	1190	53,000	164	19	163	169	40	258
j:3313	Justyd	6200	497	53,731	129	15	151	155	42	290
j:3327	Justyd	7134	943	44,873	165	9	142	128	35	222
j:3491	Justyd	8071	880	50,540	133	10	151	159	39	252
j:3768	Justyd	9857	589	42,359	130	15	147	150	31	210
j:379	Justyd	2991	1206	46,931	117	9	154	184	35	236
j:381	Justyd	2559	469	34,469	104	10	114	186	28	177

Table 1. Continued

Sample	Site	Ti	Mn	Fe	Zn	Th	Rb	Sr	Y	Zr
j:435	Justyd	5981	982	34,835	95	11	116	169	27	209
j:466	Justyd	6321	1323	39,099	219	13	132	163	30	195
j:468	Justyd	7176	817	39,168	74	8	106	153	30	178
j:526	Justyd	6691	686	47,090	174	18	159	164	34	257
j:538	Justyd	8989	196	51,545	193	12	155	124	42	263
j:735b	Justyd	7485	581	47,716	102	23	178	82	49	229
j:i17	Justyd	3248	396	33,071	32	9	95	116	26	141
t:025	Tzaram	6220	878	38,883	50	12	122	338	29	282
t:026	Tzaram	6709	408	45,789	91	17	172	202	51	545
t:027	Tzaram	7008	990	36,726	35	13	119	287	30	261
t:028	Tzaram	3212	1344	6273	140	13	165	172	48	281
t:029	Tzaram	5895	405	43,622	71	10	143	291	27	290
t:030	Tzaram	6823	1002	42,335	81	9	138	261	33	442
t:031	Tzaram	5358	527	24,813	49	9	103	255	29	184

"nd" = stands for not detected.

models to the PCA scores, it must be realized that in many compositional studies, multivariate normality is implicitly or explicitly assumed at some point in the statistical analysis. It is a common assumption that the log-transformed data are multivariate normal (Bieber *et al*., 1976; Pollard, 1986). Mahalanobis distance methods for determining group membership also commonly assume multivariate normality (Baxter, 2000; Bieber *et al*., 1976).

While there are advantages to using the classification maximum-likelihood approach, there can also be disadvantages. While MCLUST can fit elliptical models to the data by using the EM algorithm, these models are computationally intensive (Fraley & Raferty, 2000). If the dimensionality is high, the VVV model may be impossible to fit due to the number of parameters to be estimated (Fraley & Raferty, 1998*b*). Also, no matter the model being fitted, the EM algorithm breaks down and can produce erroneous results when the covariance matrix of one of the components becomes singular, or is nearly singular (Fraley & Raferty, 1998*a*, *b*, 2000). Finally, while the software can fit normal distributions to the data, the resulting groups can be meaningless if the true distribution is non-normal (Taylor, n.d.).*

Cluster validity was ascertained using quadratic discriminant analysis (QDA) with cross-validation. QDA, unlike linear discriminant analysis (LDA), does not assume that the covariance matrices of the groups are equal (Baxter, 1994). Cross-validation was used in order to develop a more robust classification rule. One drawback to QDA is that it requires a large sample size though.

*Whether it is a disadvantage or not, other than the study by Papageorgiou *et al*. (2000), no examples of using classification maximum-likelihood clustering were found for archaeometric or geochemical data. As noted by Papageorgiou *et al*. (2000) and the reviewers of this article, it is uncertain how this method performs for complex, high dimensional geochemical data. The cases reviewed in Fraley & Raferty (2000) were all situations where the data was of a few dimensions.

Table 2. First five principal components of the variance-covariance matrix of the log-transformed chemical data

Components	Eigenvalue	Variance (%)	Total variance (%)
1	13·898	46·46	46·46
2	5·475	18·30	64·76
3	3·511	11·74	76·50
4	2·875	9·61	86·11
5	1·934	6·47	92·57

Compositional Data and Analysis

Table 1 contains the minor and trace element data for each sherd. All values are listed in parts per million (ppm). In the majority of samples Pb was below the detection limit and is not reported here.

PCA of the covariance matrix of the log transformed chemical data indicates that the first five components contain 91% of the variance. Table 2 contains the eigenvalues and the variability accounted for by each factor. A plot of the first two principal components is in Figure 2.

Examination of Figure 2 suggests the presence of outliers. Before seeking clusters in the data, box-plots were generated for the first five principal component scores and the outliers removed from further analysis (see Figure 3 for an example).* In a box-plot, all cases greater than 1·5 times the inter-quartile range are identified as an outlier. Table 3 lists the outliers found and removed from the cluster analysis.

All six of the multivariate normal models were fitted to the first five PCA scores for the remaining 67 cases.

*While MCLUST has the capability to deal with outliers and noise (Fraley, 1999; Fraley & Raferty, 1998*a*, 1998*b*, 2000), this approach was not adopted here. As noted by the reviewers, it is quite possible that one of the resulting clusters could contain nothing but outliers and in essence be un-interpretable.

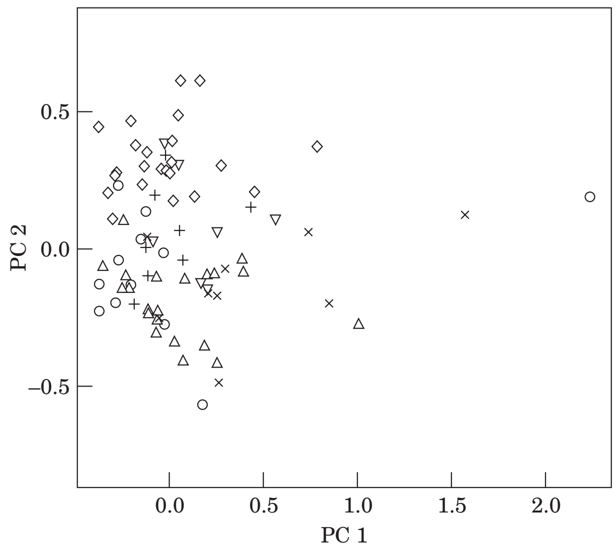

Figure 2. Plot of the first two principal component scores. The Derstui site is marked by a ○ symbol; Dureny I site is denoted by a △ symbol; Dureny II is marked by a + symbol; Ivolga is denoted by a × symbol; and Tzaram is marked by a ▽. A ◇ symbol denotes samples belong to the Justyd site.

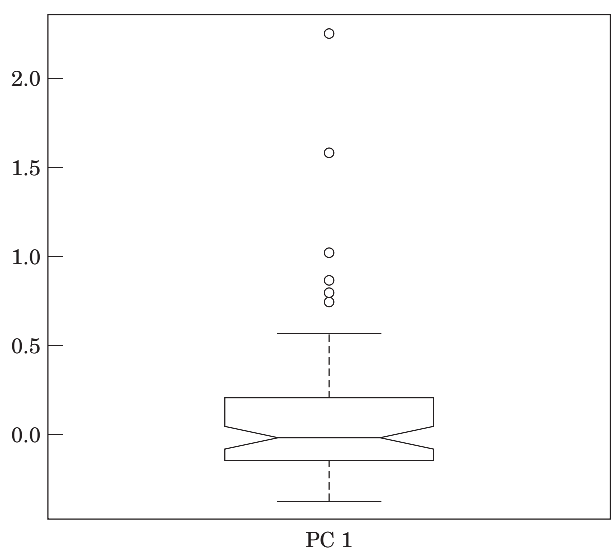

Figure 3. Box-plot for the first principal component. These were created for the first 5 PCs and the outliers removed from the classification maximum-likelihood clustering. The notched line indicates the median.

Initially, it was assumed that there is between 1 and 10 clusters in the PCA scores. Most models were found to contain singularities when more than 5 or 6 clusters were fitted; therefore, the program was re-run assuming 1–5 clusters were present.

The three best BIC values and their associated models are presented in Table 4. The BIC score positively favours the VI cluster model with three spherical clusters, each having a different volume.

Table 3. Outliers detected by the box-plot method. The first column contains the case number, while the second column lists the principal component on which it was detected as being an outlier

Case	PC outlier
d:009b	1
d1:003	3
d1:034	5
d1:037	1
iv:016	1
iv:017	1
iv:018	2
iv:024	1
j:146	5
j:190	3
j:538	3
j:i17	1
t:028	5

Table 4. The three largest BIC values and their associated models. See text for the meaning of the model abbreviations

BIC value	Model	Number of groups
199·10	VI	3
193·65	EI	3
188·95	VI	2

Table 5. Misclassified cases from the QDA of the three cluster VI model

Specimen	Cluster	Predicted group	Probability of predicted group membership
d:014a	1	2	98·9%
j:468	3	2	67·1%
t:025	3	1	91·0%
t:029	2	3	81·5%

The next best model is one having three spherical clusters with each having equal volume. This latter model corresponds to using Ward's method, which is a commonly used technique in archaeometric studies.

For the VI three-cluster model, QDA with cross-validation of the principal component scores correctly classifies 94% of the cases (63 out of 67 cases). The misclassified cases for the three-cluster VI model are listed in Table 5. QDA for the EI three-cluster model correctly classifies 56 out of 67 cases, or 83·6%. Given the higher BIC score and higher success in classification, only the three-cluster VI model will be discussed further.*

*During the data analysis, a similar figure to Figure 4 was examined for the three-cluster EI and two-cluster VI models. In the three-cluster EI model, all three clusters overlapped with each other in all projections. For the two-cluster model there was overlap at the 95% probability level for the two groups.

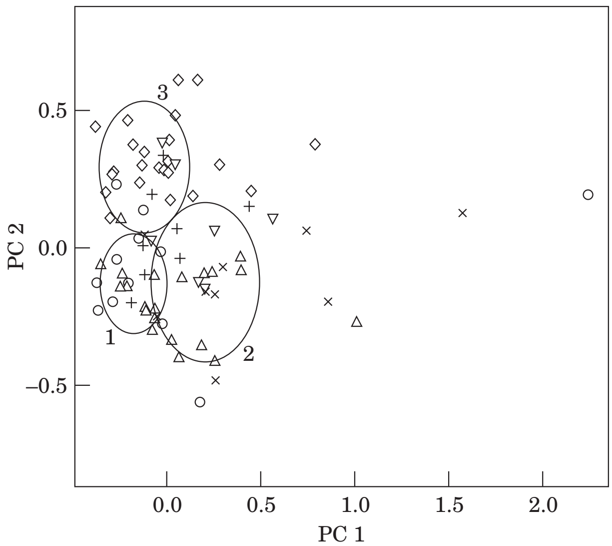

Figure 4. Plot of the first two principal component scores with the 95% probability level for the three spherical clusters (VI model) denoted. The key for the symbols is the same as Figure 2. The probability levels have a slight oblate shape due to the aspect ratio of the x-y axes.

Figure 4 is a plot of the first two principal components with the three clusters from the classification maximum likelihood clustering denoted. The circles represent the 95% probability level for each cluster. There is a slight amount of overlap between clusters 1 and 2; this is seen in other views of the principal component scores.

Table 6 lists the mean chemical composition of each group. For clusters 1 and 2, assuming a significance level of 95% ($\alpha=0{\cdot}05$) and a power equal to 0·80 ($\beta=0{\cdot}8$), a two-sided t-test indicates that there are significant differences in the mean and variance for the Fe, Mn, Rb, Zn, Y and Zr contents. For clusters 1 and 3, assuming a significance level of 95% ($\alpha=0{\cdot}05$) and a power equal to 0·80 ($\beta=0{\cdot}8$), a two-sided t-test indicates that there are significant differences in the mean and variance for the Rb, Sr, Ti and Y contents. With the same assumptions, for clusters 2 and 3, a two-sided t-test indicates that there are significant differences in the mean and variance for the Fe, Rb, Sr, Th, Ti, Y and Zn. Cluster membership for the 67 cases is listed in Table 7.

Table 7. Cluster membership for the three cluster VI model

Cluster 1	Cluster 2	Cluster 3
d:009	d:009a	d:014a
d:009c	d1:005	d:014d
d:010	d1:007	d2:050
d:011	d1:033	d2:051
d:011a	d1:035	j:106
d:011b	d1:036	j:139
d:014b	d1:038	j:1475
d:014c	d1:039	j:1624
d1:001	d1:040	j:216
d1:002	d1:042	j:3102
d1:004	d1:045	j:316
d1:006	d2:046	j:3259
d1:008	d2:047	j:3313
d1:041	d2:050	j:3327
d1:043	iv:015	j:3491
d1:044	iv:020	j:3768
d2:048	iv:022	j:379
d2:049	j:381	j:435
d2:053	t:025	j:466
iv:019	t:027	j:468
iv:023	t:029	j:526
t:030	t:031	j:735b
		t:026

Discussion

Using the classification maximum-likelihood approach, a three-cluster model consisting of spheres with varying volumes (VI) was found to fit the data the best. The next best model fitting the data was a three-cluster model with spheres of equal volume (EI). This latter model corresponds to hierarchical clustering using Ward's algorithm. While the three-cluster VI model had a higher classification rate, QDA found the classification success rate for the three-cluster EI model being over 80%.

A frequency table of the chemical groups versus sites is contained in Table 7. Note that clusters 1 and 2 are

Table 6. Mean chemical compositions for the three groups found by classification maximum likelihood clustering. All values, including the standard deviation (std), are expressed in parts per million (ppm)

Element	Group 1 (n=22) Mean	Std.	Group 2 (n=22) Mean	Std.	Group 3 (n=23) Mean	Std.
Ti	8477	2536	6492	1945	6740	1928
Mn	1121	348	804	291	902	311
Fe	52,852	10,381	36,896	7230	45,842	7563
Zn	116	21	71	22	136	40
Th	12	5	10	5	15	6
Rb	136	27	109	30	157	21
Sr	431	114	398	192	175	54
Y	33	5	25	6	39	8
Zr	313	53	206	48	274	85

Table 8. Frequencies of each chemical group found at each site. Further statistics are not calculated since more than 20% of the cells have expected frequencies less than 5

Site	Group 1	Group 2	Group 3
Derstui	8	1	2
Dureny I	8	10	0
Dureny II	3	3	2
Ivolga	2	3	0
Justyd	0	1	18
Tzaram	1	4	1

primarily found at the sites in the Trans-Baikal region, while cluster 3 is concentrated at the Justyd site. If the "criterion of abundance" (Bishop, Rands & Holley, 1982) holds, one can postulate that clusters 1 and 2 reflect the use of regional clay deposits in the Trans-Baikal region, and cluster 3 represents the use of a regional clay deposit in the Altai region.

With this in mind, the distribution pattern in Table 6 would suggest there was some *limited* pottery movement between sites in the Xiong-nu confederacy. The driving force behind this movement is uncertain though. As Renfrew (1977) illustrated with ethnographic examples, there are a variety of ways and reasons for pottery to be transported from settlement to settlement in early state societies. Given the lack of elaborate designs and the relative similarity of pottery over the areas controlled by the Xiong-nu, we do rule out the pottery having any intrinsic value, or being a symbol of rank or status. One possible explanation is that the pottery was used as containers for goods that were exchanged or redistributed. One such good could have been grain. Despite stereotypes, agricultural products are a necessary supplement in any nomad's diet (Di Cosmo, 1994; Khazanov, 1978). As documented by archaeological finds of ploughshares at Ivolga (Davydova, 1995) and grain stored in pottery at Noin Ula (Trever, 1932), at least some segments of the Xiong-nu confederacy practiced agriculture.

Other explanations are also possible. Pottery movement may also have occurred due to the movement of people between sites. Seasonal movements across the landscape (Reid & Montgomery, 1998; Zedeño, 1992), or alternatively, some mechanism such as bride-wealth or the movement of marriage partners (for ethnographic examples in Central Asia see Abramzon, 1978; Argynbaev, 1978) could have been the driving force for pottery movement. Finally, the three different groups of pottery found in the burials at Tzaram could be interpreted as having held tribute for the deceased. If Tzaram were a cemetery for the *shan-yu*, then it would be quite feasible that burial goods were drawn from across the Xiong-nu confederacy. As more pottery samples are analysed, more meaningful patterns should emerge.

Conclusion

From a methodological viewpoint, this paper demonstrates the utility of the classification maximum-likelihood approach. Like the work by Papageorgiou *et al.* (2000), interpretable results were obtained when low dimensional data was used and outliers were identified and removed from the analysis.

The results of the classification maximum-likelihood cluster analysis presented here indicate that there are three spherical clusters of varying volume in the chemical data. These clusters are interpreted as regional clay resources that were exploited by numerous Xiong-nu groups. The distributional patterns indicate that there was limited movement of pottery between the eastern and western parts of the Xiong-nu confederacy. Whether the pottery was used as containers for some sort of "trade goods", or moved in the course of the nomad's seasonal rounds, is uncertain at this time.

These results are only a starting point for understanding trade and exchange within the Xiong-nu confederacy. More pottery samples from Xiong-nu settlements and cemeteries in the Altai region and Mongolia need to be analysed. In addition, other types of analytical work are needed. Petrography would also provide insights into the types of raw materials used to manufacture the pottery (see for example Day *et al.*, 1999; Williams *et al.*, 1974). The use of techniques such as neutron activation analysis (NAA) and inductively coupled plasma spectroscopy (ICP), both of which can measure the rare earth elements, may be able to further refine and sub-divide the three groups found here. Once production workshops are defined, scholars can then begin to build more substantive models of interaction during the Xiong-nu era both between the Xiong-nu confederacy and Han Empire, and within the Xiong-nu confederacy itself.

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Appendix

The detection limits for the given operating conditions, as determined on geological standards, are as follows: Fe 500 ppm, Mn 100 ppm, Pb 30 ppm, Rb 5 ppm, Sr 20 pm, Th 8 ppm, Ti 500 ppm, Y 7 ppm, Zn 15 ppm, and Zr 7 ppm.

The table below provides the results of the standards run with the unknowns. This was done to maintain and monitor accuracy and precision. The results are:

Element	JG2 (this study) $n=5$	JG2 (Hallet & Kyle, 1993)	Accuracy %
Ti	nd	359	—
Mn	221	232	4·8
Fe	7178	6785	5·8
Zn	nd	13	—
Pb	32	30	6·7
Th	31	29·9	4·4
Rb	293	291	0·82
Sr	nd	16	—
Y	86	85	1·2
Zr	91	88	2·6

Element	JB3 (this study) $n=9$	JB3 (Hallet & Kyle, 1993)	Accuracy %
Ti	10,712	8632·8	25·1
Mn	1317	1316·0	0·08
Fe	89,363	82184·2	8·7
Zn	82	95	13·2
Pb	nd	4·5	—
Th	nd	1·21	—
Rb	17	14	12·2
Sr	389	417	6·7
Y	28	28	0·0
Zr	96	97	0·69

nd = not detected.