

# Network Analysis of Archaeological Data from Hunter-Gatherers: Methodological Problems and Potential Solutions

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Published online: 7 January 2015

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**Abstract** Network analysis using hunter-gatherer archaeological data presents a number of unique challenges. At the forefront of these challenges are issues associated with the aggregation and fragmentation of archaeological data that influence the size, density, and confidence in network models. These methodological challenges are unfortunate, as the diverse roles of social networks among hunter-gatherers have long been recognized within anthropological research. In order to enhance the research potential of networks constructed from hunter-gatherer archaeological data, this research highlights two data evaluation methods established in social science research to assess the stability of network structure. More specifically, this research constructs network models from the compositional analysis of ceramic artifacts recovered in the Kuril Islands of northeast Asia and evaluates network centrality measures using bootstrap simulation and sensitivity analysis. Results of this research suggest that while archaeologists may never fully identify the “true” network of past relationships, network models that approximate “true” network structure can provide useful metrics in exploring the behavior of past hunter-gatherer populations. Overall, given the challenges associated with hunter-gatherer archaeological data, it is argued here that critically evaluating the structure and stability of network models is an essential first step in developing an *archaeological network analysis* that is relevant and informative to research on past small-scale societies.

**Keywords** Network analysis · Hunter-gatherers · Kuril Islands · Compositional analysis

## Introduction

Over the past decade, the range of academic disciplines applying a network perspective has grown exponentially from its origins in social science to a diverse collection of

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disciplines including physics, biology, business, and economics. The common appeal of network analysis, including social network analysis (SNA), for many of these disciplines is that it provides a set of unique methods for visualizing and measuring sets of relationships (Wasserman and Faust 1994). In particular, the growth of network analysis within social science research has been influenced by advancements in computing that can efficiently analyze the complex social relations that characterize human populations. Within archaeology, network analysis has been broadly applied to populations ranging in space and time from Mesoamerica (Golitzko *et al.* 2012; Scholnick *et al.* 2013) to the Middle East (Knappett and Nikolakopoulou 2005; Collar 2013) and from the Epipaleolithic (Coward 2013) to the present (Mol and Mans 2013).

While network analysis methods continue to be applied in a variety of archaeological contexts, it is important to understand that not all archaeological datasets are equally amenable to network analysis (Mills *et al.* 2013). For instance, in many archaeological applications of SNA, archaeological databases used for analysis have been drawn from either historic contexts or detailed textual records that directly indicate trade or social relationships (Coward 2013). However, in many archaeological datasets, direct insights into past social relationships are not always so obvious. Networks constructed from archaeological data are more commonly visual representations of connections inferred from a variety of assumptions about how individuals or sites in the past are related by material culture. These assumptions can become increasingly problematic when examining the scant material evidence of mobile foraging societies, but they do not inherently prohibit network analysis. This research aims to demonstrate that given the appropriate methodological considerations, network structures can be reconstructed from hunter-gatherer material culture and used to inform and enhance archaeological interpretations.

### **Hunter-Gatherer Social Networks: Function and Form**

Despite the limited application of formal network analysis to hunter-gatherer archaeological data, the concepts of social relationships and material exchanges have long been of interest to anthropologists studying small-scale societies (Braun and Plog 1982; Lévi-Strauss 1969; Malinowski 1953; Mauss 1954; Radcliffe-Brown 1952; Wiessner 1977). As highlighted by Wobst (1974), Rautman (1993), and Wiessner (1977, 1982) among others, perhaps one of the most fundamental roles of social relationships within small-scale societies is minimizing the influence associated with incomplete knowledge. Perhaps most well known is the *hxaro* exchange system (Wiessner 1977, 1982, 1998, 2002), where reciprocal exchange partnerships serve as a mechanism for the sharing of environmental information across local, regional, and distant spatial scales with each individual actively maintaining social network partners (Wiessner 1997). Through reciprocal gift giving, these exchange partners are formalized and act as a support network that can provide places of refuge for individuals when physical hazards impact local subsistence resources. As discussed by Wobst (1974) and Rautman (1993), social networks within small-scale societies also help in reducing the impact of uncertainty in the marriage pool by providing information about available mates among other groups. In these cases, the actual amount of material goods or

partners that are exchanged may be minimal, but the network still serves as a regional redistribution mechanism (Rautman 1993). In addition to mating networks, social networks have also been suggested to function in the reduction of uncertainty associated with violent behavior. As emphasized by Baksh and Johnson (1990), one response to inter-personal violence among hunter-gatherers includes extensive inter-household or inter-group exchanges, which provide a mechanism for gaining knowledge concerning individuals in other households or groups. The development and sharing of this knowledge helps to mitigate inter-personal and group violence by allowing peaceful individuals to more easily avoid violent individuals as well as developing a network of trusted partners that can help resolve passive or active violent behavior.

Undoubtedly, social networks among foraging populations likely functioned in a multitude of different roles from not only information-sharing networks or social safety networks but also advice networks, food redistribution networks, political alliance networks, and kinship networks to name only a few. Given the potentially infinite number of networks within small-scale societies that may or may not leave material traces, it is often impossible for an archaeologist to assume *a priori* what type of social relationships, if any, are being represented within an archaeological assemblage. For some archaeologists, inferring the function of networks based upon archaeological data from hunter-gatherers can quickly become a suspicious exercise that is highly influenced by difficult assumptions including the ability to establish contemporaneity between archaeological sites, the inability of scant archaeological evidence to reveal social relationships, and/or the sampling or excavation strategy of the researcher. In my own experience, colleagues have often highlighted these deficiencies with commonly encountered questions such as “How do you know that certain artifacts are good indicators for inferring social relationships?” “How do you know what the network was used for?” “Don’t you think you need more data before you can reconstruct a social network from 3000 years ago?” Based upon these limitations of archaeological data, it is accepted here that archaeologists will rarely ever know the “true” function (or functions) of a social network as relationships among individuals are extremely diverse, constantly evolving, and difficult to access through material traces. However, it is argued here that the inability to identify the exact type of social relationship should not exclude network analysis from the archaeological toolkit but rather places a greater emphasis on building confidence in the form or structure of archaeological networks.

The use of hunter-gatherer archaeological data may have limitations in conceptualizing the function of past network relationships, but it should be encouraging for archaeologists to know that the construction of network form from archaeological data suffers from many of the same problems encountered by social scientists using more conventional datasets. As all archaeologists are keenly aware, interpretations of the archaeological record are often based on material culture that is temporally aggregated. Thus, the construction of any discrete archaeological network model is also based on artifact assemblages comprised of artifacts from a wide range of temporal contexts. Similarly, since the early development of social network analysis, the temporal aggregation of social ties in a network model has also been problematic (Marsden 1990). The central concern to both archaeologists and sociologists is whether a static network model of aggregated social connections or artifacts can be considered “a persisting order or pattern of relationships among some unit of sociological analysis” (Laumann and Knoke 1986, p. 84). In archaeological research, the assumption of persistent

relationships is often taken to an extreme with networks representing hundreds if not thousands of years of interactions and material exchanges between individuals. In order to overcome these fundamental issues, it is often acknowledged in social network analysis that social exchange can occur as episodic or momentary interactions between individuals, but the relationships identified by researchers are likely the most routinized or consistently reproduced interactions (Huston and Robins 1982). It is recommended here that archaeologists adopt a similar assumption when modeling networks in that material or information exchanges that were more consistently performed in the past have a greater chance of recognition hundreds or thousands of years after their last occurrence.

Related to the aggregation problem, archaeologists are often faced with a fragmentation problem. In this research, the fragmentation of data refers to variation in the availability and types of data between units of archaeological analysis. The fragmentation problem is particularly challenging in developing network structures based on small-scale, hunter-gatherer societies given their increased mobility, small population sizes, and reduced material culture signatures. In the terminology of social network analysis, the fragmentation problem can be framed as a missing data problem, with a fundamental question of how do we know if all the relevant actors (or archaeological sites) have been identified? Given the relational nature of social networks, the inappropriate inclusion or exclusion of a small number of entities can potentially have significant ramifications on the structural properties of a network (Butts 2008). In addressing this question, many networks used for analysis within social sciences maintain exogenously defined boundaries where membership is fairly well understood so that it is possible to obtain relevant information on many of the network nodes and that the failure to record a single tie or node does not lead to a radically different understanding of the network structure. Based upon this assumption, a majority of social network research defines the boundaries of a network by the set of actors on which measurements can be obtained. In contemporary situations, when the boundary of a network is unknown, special research designs and survey methods can be utilized, such as respondent-driven or snowball sampling that helps define network boundaries or highlights hidden populations (Heckathorn 1997, 2002). In archaeological research, exogenously defining the boundaries of a network often means evaluating a sample of archaeological sites within a geographic region or limiting analysis of archaeological sites that correspond directly to a cultural or temporal period.

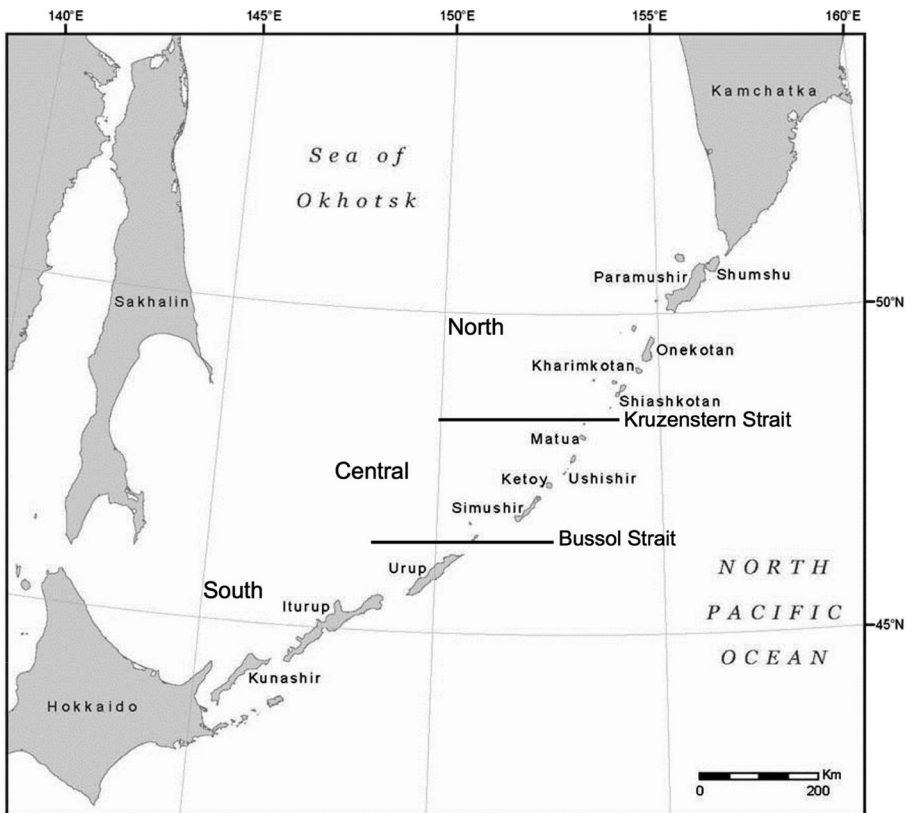
## **Reconstructing Hunter-Gatherer Network Structures from Archaeological Data in the Kuril Islands**

### The Kuril Islands

As acknowledged above, construction of network form using archaeological data from hunter-gatherer contexts is influenced by the aggregation and fragmentation of archaeological data. One of the main contributors to the severity of aggregation and fragmentation problems is the amount of archaeological work performed in a region and the availability of relevant archaeological data. The vast majority of archaeological data used in this research stems from archaeological fieldwork in the Kuril Islands of

northeast Asia (Fig. 1) conducted by the Kuril Biocomplexity Project (KBP) between 2006 and 2008. Over the course of three field seasons, the KBP undertook comprehensive survey and excavation of archaeological sites in the southern, central, and northern regions of the island chain (Fitzhugh *et al.* 2007, 2009a, b). Based upon this field research, over 60 archaeological sites were identified throughout the archipelago. However, given active taphonomic processes as well as the fragmented archaeological record of mobile hunter-gatherers, only 20 archaeological sites contained obsidian or pottery remains which were suitable for inferring exchanges between past hunter-gatherers communities using geochemical sourcing methods. Among these 20 archaeological sites, 12 had moderate to large artifact assemblages due to intensive excavation or surface collection with the remaining eight sites containing less than 20 pottery sherds or obsidian artifacts.

Based upon radiocarbon data provided by the KBP, the 20 archaeological sites used in this network analysis chronologically extend over 3000 years and include the two longest and most intensive occupation periods of the archipelago, 2550–1300 and 1300–700 cal BP. Using similarity in pottery styles between the Kuril Islands and the neighboring islands of Hokkaido and Sakhalin, these occupation periods are associated with the Epi-Jomon (2500–1300 cal BP) and Okhotsk (1300–700 cal BP) cultures. In



**Fig. 1** Map of the Kuril Islands showing major open water straits, geographic regions, and names of key islands

brief, the Epi-Jomon culture is widely viewed as a continuation of hunter-gatherer subsistence practices in Hokkaido and the Kuril Islands after the widespread adoption of rice agriculture in the Japanese islands (Aikens and Higuchi 1982; Habu 2004). In contrast, populations associated with the Okhotsk culture are often considered to have migrated to Hokkaido and the Kuril Islands after originating in the western Sea of Okhotsk (Deryugin 2008; Hudson 2004). As a note, due to very limited pottery and obsidian assemblages, occupations of the Kuril Islands associated with the Jomon (Middle, Late, and Final) and Ainu periods are not included in this analysis.

Perhaps the most defining feature of the Kuril archipelago is the biogeographical differences between regions of the island chain. Stretching between the island of Hokkaido and the Kamchatka peninsula, the Kuril Islands comprise approximately 32 islands that vary in size from 5 to 3200 km<sup>2</sup> with regions separated by two major open water straits, the Bussol and Kruzenstern. In addition to geographically dividing the southern and central regions, the Bussol Strait also serves as an major ecological barrier that significantly influences modern flora and fauna distributions (Pietsch *et al.* 2003). Compared to the very low biological diversity of the central and northern Kuril Islands, the southern islands demonstrate substantially higher flora and fauna diversity with a wide range of mammals, birds, insects, fish, and shellfish (Hoekstra and Fagan 1998; Pietsch *et al.* 2003). As part of the extremely active Kuril-Kamchatka subduction zone, major tectonic events are a common occurrence in the island chain, and it is likely these events were frequent throughout the Middle and Late Holocene (Fitzhugh 2012; MacInnes *et al.* 2009). Over the last 3000 years, Nakagawa *et al.* (2008, tDAR) has documented approximately 80 major volcanic eruptions across the island chain with six eruptions classified as caldera or large Plinian eruptions. In addition to volcanic eruptions, paleo-tsunami deposits in the central islands indicate the regular presence of tsunami events similar in scale to a couplet of 20 m tsunami waves that struck the island chain in 2006 and 2007 (MacInnes *et al.* 2009). While less catastrophic than tectonic hazards, weather strongly influences habitation and movement in the region (Fitzhugh 2012). During winter months, two strong atmospheric systems interact creating northerly winds that bring in cold air masses from the Asian continent and produce nearly 138 snowstorm days per year and stable snow cover from November to May (Ganzei *et al.* 2010; Leonov 1990; Razjigaeva *et al.* 2008). In the summer months, due to the interaction of the cold Oyashio current and the warm Soya current, some areas of the Kuril Islands experience nearly 215 fog occurrence days per year, statistically making the archipelago one of the foggiest places on earth (Bulgakov 1996; Razjigaeva *et al.* 2011; Tokinaga and Xie 2009).

### Compositional Analysis of Kuril Pottery

The use of geochemical sourcing data to infer the structure of relationships between archaeological sites in the Kuril Islands differs from more traditional methods that use a combination of technological and stylistic similarities (Mills *et al.* 2013; Mizoguchi 2009). In contrast to these network models, the use of geochemical sourcing data relies upon tracing the flow of material goods rather than the flow of information. Network ties are constructed based on the movement of pottery sherds between their location of geologic origin and their location of archaeological recovery. The linking of archaeological sites based on elemental characterization does require that clay geochemistry

clearly demonstrates real spatial differences between archaeological sites. However, depending on a variety of factors, the ability to clearly identify spatial patterns within geochemical data of clay can be easily masked by differing methods of elemental analysis, underlying regional geology, the formation of clay deposits, and/or the anthropogenic alteration of clay resources. It is important to note that the use of sourcing data does not inherently assume any type of specific social relationship that is responsible for the movement of a pottery vessel but rather simply acknowledges that the vessel was transported from one location to another. This research does assume that when a pottery sample recovered at one archaeological site is reliably assigned to a geochemical source group associated with a different archaeological site, the transportation of the sample is most likely attributable to movement by cultural rather than natural processes.

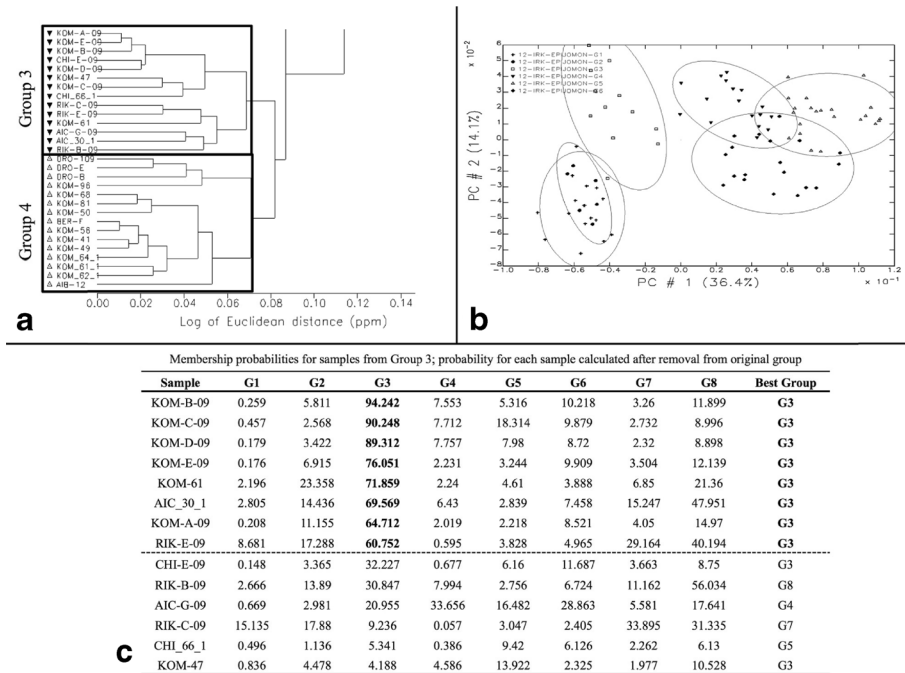
Unlike previous obsidian studies in the region that reveal long-distance, non-local relationships, (Phillips 2011; Phillips and Speakman 2009) exchange networks derived from ceramic source data can better highlight relationships at the local, supra-local, and regional levels within the island chain. This increased spatial resolution from pottery data occurs because obsidian sources are not found locally in the Kuril archipelago with obsidian only entering the island chain from external sources on Hokkaido and Kamchatka. Therefore, obsidian data is perhaps more relevant to network relationships located at the ends of the archipelago and is less informative about the exchange relationships among sites within the island chain (Gjesfeld and Phillips 2013). Tracing the movement of pottery sherds from their original clay sources to their place of archaeological deposition can therefore provide a general measure of the distance and direction of pottery movement between archaeological sites as well as a basis for inferring network ties between hunter-gatherer populations.

In this research, the procedure for establishing network ties between archaeological sites is based upon the protocol for geochemical source group identification established by the Archaeometry Laboratory at the University of Missouri Research Reactor (MURR) (Baxter and Buck 2000; Glascock 1992; Glascock *et al.* 2004). Construction of network models for this research began by obtaining the trace element concentrations for 297 pottery samples using inductively coupled plasma-mass spectrometry (ICP-MS) at the Institute of the Earth's Crust, Russian Academy of Sciences-Irkutsk (IEC-RAS). Using elemental characterization data, the grouping of pottery samples into source groups relies on the use of multivariate statistics including cluster analysis and principal components analysis (PCA). Given the presence of correlated elements as well as variability in distance measurements and clustering algorithms, cluster analysis is only used to identify initial groupings with PCA methods used for further refinement and classification of geochemical source groups. Once initial cluster groups are formed based upon all elemental concentrations (Fig. 2a), PCA techniques are used to reduce dimensionality of the dataset to a smaller number of uncorrelated variables and to identify key elements that are driving the principal variation in the data (Glascock *et al.* 2004). Biplots of key principal components (Fig. 2b) provide a visual representation of groupings within the data allowing for evaluation of group memberships assigned through cluster analysis. Final group membership is ultimately determined by calculating the probability of each sample belonging to its assigned group through the use of Mahalanobis distance (MD). In general, the MD statistic incorporates information between pairs of elements and permits calculating the probability that

a sample belongs to the assigned group based not only on its proximity to the centroid of the group but also on the rate at which the density of the sample data points decreases away from the centroid (Glascok *et al.* 2004). The use of MD is preferred as Euclidean distances do not account for correlations between elemental variables. Once group membership is established through MD probabilities, network ties between archaeological sites were assigned based upon source group composition. Using a majority rule, network ties were given between all samples in the same group with membership probabilities over 50 % with the assumption that these samples are the most likely to share the same geologic place of origin. As identified in Fig. 2c, eight of 14 samples in source group three (G3) have high probabilities of belonging to the group with network ties established between the archaeological sites of Kompaniskii (KOM), Ainu Creek (AIC), and Rikorda (RIK). Furthermore, given that 75 % of these high probability samples are from a single archaeological site (KOM), it is likely that the geologic origin of all these samples is near the site of Kompaniskii based upon the “criterion of abundance” (Bishop *et al.* 1982).

**Assessing Confidence in Small-Scale Networks**

The effect of aggregation and fragmentation issues on the analysis of archaeological networks is a lack of confidence in the structure of network models. Fortunately, these data concerns are not unique to archaeological research and remain common topics of



**Fig. 2** a Cluster analysis showing preliminary source groups. b Biplot of the first two principal components showing source group clusters with 90 % confidence ellipses c Table of membership probabilities for group 3 based on Mahalanobis distance (dashed line represents 50 % threshold for group membership; bold values indicate pottery samples from group 3 used in network construction)



discussion within many social science disciplines that utilize social network analysis. Based upon methodologies established in these related disciplines (Costenbader and Valente 2003; Borgatti *et al.* 2006), this research favors the construction and evaluation of longitudinal data (if possible) for minimizing aggregation effects and the use of bootstrap simulation and sensitivity analysis for assessing fragmentation effects. Statistical routines associated with bootstrap simulation and sensitivity analysis were completed using the freely available R statistical environment (R Development Core Team 2010) with analysis and visualization of network graphs performed using the *statnet* statistical package for R (Handcock *et al.* 2003)

### Aggregation Within Kuril Island Networks

Given the inherent aggregation of archaeological data, one of the first considerations prior to analyzing and interpreting networks is how many networks are appropriate to summarize the social relationships that occurred during occupation of the research area? In general, two different approaches have been used in addressing this issue. At one end of the spectrum, archaeologists have assumed a long-term static bias in social relationships with an implicit emphasis on the routinized or consistently reproduced relationships. In this scenario, a single network represents all the social relationships that occurred during the time period of interest. At the other end of the spectrum, archaeologists have developed longitudinal network data that produces multiple networks that are each associated with discrete time periods.

If possible, the development of longitudinal network data is highly encouraged as it can provide valuable insights into the evolution of network structure. For example, the pioneering work of Mills *et al.* (2013) in the Tonto and San Pedro valleys of the American Southwest analyzes four distinct networks that are associated with discrete 500-year periods (AD 1200–1250; AD 1250–1300; AD 1300–1350; AD 1350–1400). Coward (2013) demonstrates a similar approach by creating multiple network indices for all sites dated to 1000-year time slices ranging between 22,000 and 6000 years ago in Europe. However, within much of the archaeological data of small-scale societies, the development of network data specific to multiple temporal intervals can be difficult to obtain given limitations in available dating evidence and uneven artifact distributions. For instance, the Kuril assemblage of 297 pottery samples from 20 different archaeological sites produces variable network sizes when subdivided into arbitrary 500-year intervals (see Table 1). Furthermore, archaeological research (Fitzhugh *et al.* 2004) suggests that the Epi-Jomon and Okhotsk populations were likely unrelated occupations and not contemporaneous. Therefore, subdividing the period from 2500 to 500 cal BP into discrete 500-year or 1000-year periods not only reduces network size but also artificially imposes a temporal structure that does not correspond to the reality of cultural occupation in the region.

Given limitations of available archaeological data suitable for elemental characterization, the construction of network models for multiple temporal periods (500-year intervals) is not feasible for this research. However, given the distinct cultural occupations recognized in the Kuril Islands, a single network that encompasses both major occupations is also questionable. In order to evaluate the suitability of a single network for both cultural periods, it is necessary to determine the similarity between the networks for separate cultural periods. If strong similarity exists between both

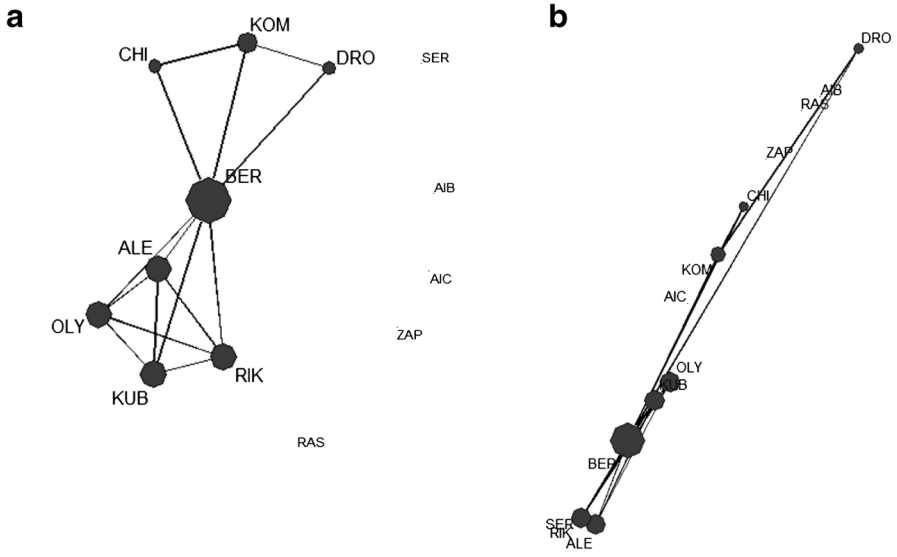
**Table 1** Range of networks and their sizes when subdividing Kuril pottery assemblage by time period and culture

|  |                          |                         |          |           |           |           |          |
|--|--------------------------|-------------------------|----------|-----------|-----------|-----------|----------|
| Temporal interval                        | 2000                     | 1000                    | 500      |           |           |           |          |
| No. of networks                          | 1                        | 2                       | 4        |           |           |           |          |
| Age ranges (cal BP)                      | 2500–500                 | 2500–1500               | 1500–500 | 2500–2000 | 2000–1500 | 1500–1000 | 1000–500 |
| Available sites/<br>nodes per<br>network | 20                       | 14                      | 15       | 15        | 12        | 14        | 10       |
| Percent of total sites                   | 100 %                    | 70 %                    | 75 %     | 75 %      | 60 %      | 70 %      | 50 %     |
| Occupation periods                       | Okhotsk and<br>Epi-Jomon | Okhotsk or<br>Epi-Jomon |          |           |           |           |          |
| No. of networks                          | 1                        | 2                       |          |           |           |           |          |
| Available sites/<br>nodes per<br>network | 20                       | 13                      | 17       |           |           |           |          |
| Percent of total sites                   | 100 %                    | 65 %                    | 85 %     |           |           |           |          |

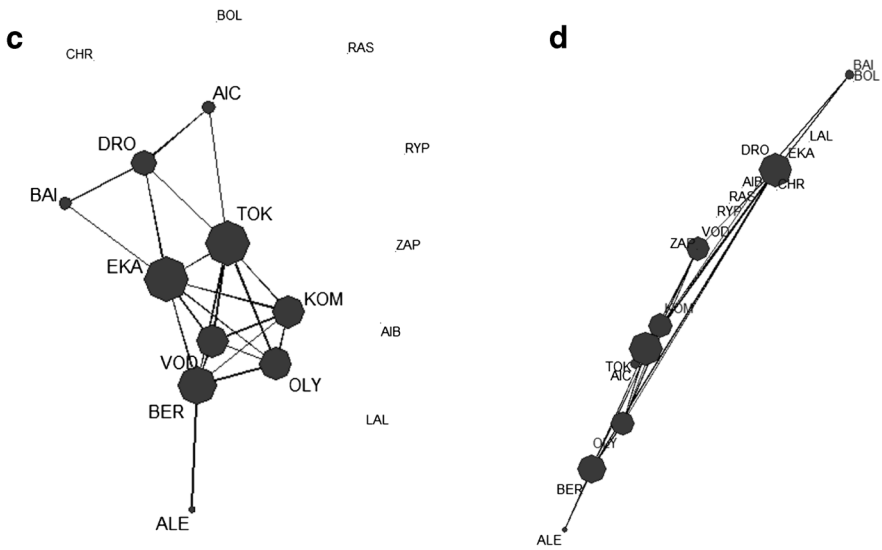
networks, it can be assumed that the structure of the networks likely remained reasonably static over time so that a single network provides an acceptable model of network ties over both cultural occupations. Perhaps the simplest method to determine the similarity between two network graphs is to determine their graph correlation. Similar to traditional correlation methods, graph correlation is obtained by dividing the covariance of the matrices by their standard deviations. The resulting statistic can be interpreted as a standard Pearson's product-moment correlation coefficient with values nearest to one suggesting an increasing positive correlation and values nearest to negative one suggesting a negative decreasing correlation with values nearest to zero suggesting independence. Results of graph correlation between the Epi-Jomon and Okhotsk networks demonstrate clear independence between the two networks with a correlation coefficient of 0.12. Based upon these results, this research favors the construction of two separate networks corresponding to each of the major cultural occupations in the Kuril archipelago (Fig. 3). Furthermore, it is assumed here that creating specific networks for each cultural period provides the greatest likelihood that archaeological sites used in this network analysis were occupied contemporaneously and potentially involved in social exchanges.

### Fragmentation Within Kuril Island Hunter-Gatherer Networks

In the construction of network form, it is often assumed that missing data does not greatly influence node and graph-level indices of the network. In other words, the failure to record a single node or a single tie does not significantly alter the network structure or measurements such as centrality (Borgatti *et al.* 2006). However, it is also known that certain centrality measures, such as eigenvector centrality, can vary significantly when only a sample of nodes is used for analysis (Costenbader and Valente 2003; Mills *et al.* 2013). Therefore, evaluating the stability of basic network measures is an important consideration for assessing the robustness of networks constructed from imperfect data (missing or hidden nodes and ties). Given the aggregation and fragmentation issues discussed in this research, hunter-gatherer archaeological data can often be



Epi-Jomon (2500-1300 calBP)  
Network size: 13 (5 isolates)  
Graph density: 0.192 (.535 w/o isolates)



Okhotsk (1300-700 calBP)  
Network size: 17 (7 isolates)  
Graph density: 0.162 (.489 w/o isolates)

**Fig. 3** **a** Epi-Jomon network graph. **b** Epi-Jomon network graph (with nodes in geographic position). **c** Okhotsk network graph. **d** Okhotsk network graph (with nodes in geographic position). Size of node is proportional to the degree centrality of that node

considered imperfect as network boundaries are often tentative and many of the nodes/sites exhibit significant variability in their attributes and assemblages. Overall, the goal for assessing the stability of network measurements on archaeological networks is to evaluate whether the network graph constructed from available archaeological data can be conceptualized as a sample of an inaccessible larger network that would include unknown or missing archaeological sites. If network centrality measures demonstrate stability across a range of sampled networks, then interpretations from the archaeologically constructed network can potentially be projected as interpretations of a larger, “real” network.

Following previous research on the stability of centrality measures (Borgatti *et al.* 2006; Costenbader and Valente 2003; Galaskiewicz 1991; Mills *et al.* 2013), this research uses a bootstrap procedure to determine how sampling influences the stability of three common centrality measures: degree centrality, eigenvector centrality, and betweenness centrality. Without reiterating research concerning centrality measurements in sociology and archaeology (Bonacich 1972; Borgatti 2005; Brughmans 2010, 2013; Freeman 1977, 1979; Freeman *et al.* 1991; Mizoguchi 2009; Peeples and Roberts 2013; Wasserman and Faust 1994), these three centrality measurements are used as they represent three different ways to conceptualize the centrality of a node. The most basic centrality measure is degree centrality, which is calculated by summing the total number of direct connections to and from a single node. Eigenvector and betweenness centrality differ slightly as they emphasize the position and connectedness of a single node in relation to other nodes and ties in the network. Betweenness centrality measures the shortest paths between pairs of nodes that include the specific node of interest (Freeman 1977). Eigenvector centrality (Bonacich 1972) differs by measuring the importance of a node based upon its indirect connections to other nodes in the network. As Peeples and Roberts (2013) note, eigenvector centrality is appealing to archaeological research as it assumes that a node is able to influence other nodes in the network simultaneously rather than through network position or direct ties (Table 2).

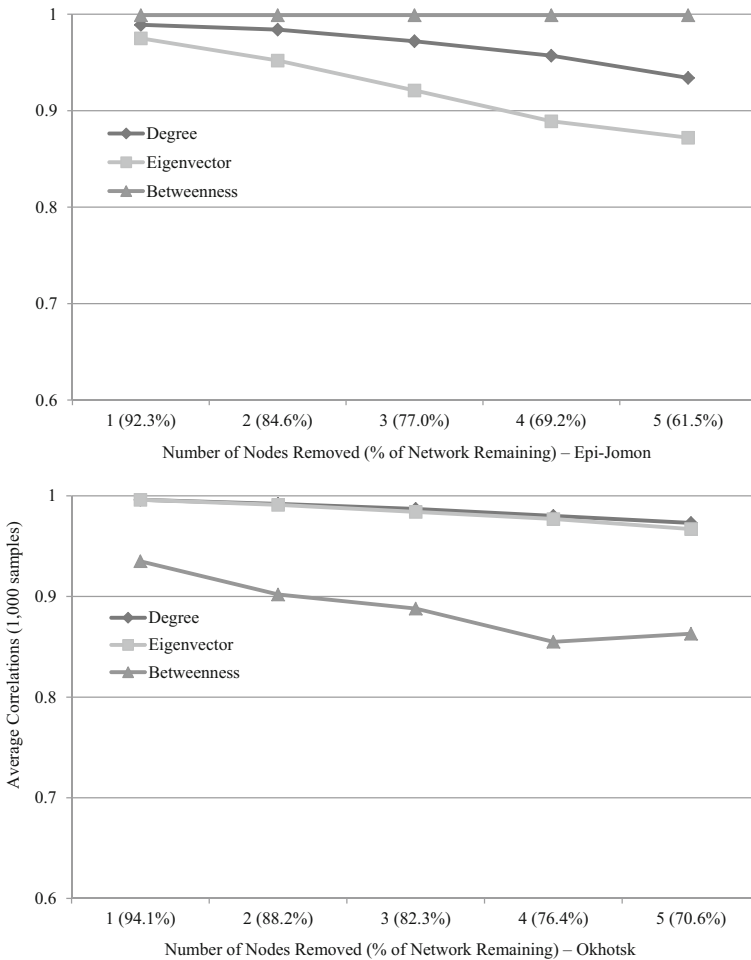
The simulation procedure used to assess network stability proceeds by calculating three centrality measures (degree, eigenvector, and betweenness) for repeated random samples of the Epi-Jomon and Okhotsk networks. The sampling process occurs by removing between one and five nodes, or roughly 5 to 40 % of the network. Given the presence of isolates as well as the small network sizes of the Epi-Jomon network (13) and the Okhotsk network (17), centrality measures after the removal of five nodes would often contain a sample network with very few ties. Following Costenbader and Valente (2003), nodal centrality measures were calculated for each sampled network and the original network, minus the sampled node(s). Once calculated, the centrality measures for each sampled network were correlated with the original network centrality. This process occurred 1000 times for each centrality measurement with a graph of average correlations for the Epi-Jomon and Okhotsk networks presented in Fig. 4.

The most significant result of the bootstrap simulation procedure is the presence of a slightly stronger decline in the average correlation values of the Epi-Jomon network. The decrease in centrality correlation among the sampled Epi-Jomon networks is most likely due to the smaller network size of the Epi-Jomon network (13 nodes) compared with the Okhotsk network (17 nodes). With fewer overall nodes, the removal of only a few nodes and their ties can more significantly alter the overall network structure. In

**Table 2** Centrality measurements for Epi-Jomon and Okhotsk networks

| Site name     | Site abbrev. | Centrality measures |             |             |
|---------------|--------------|---------------------|-------------|-------------|
|               |              | Degree              | Eigenvector | Betweenness |
| Epi-Jomon     |              |                     |             |             |
| Berezovka     | BER          | 14                  | 0.50        | 25          |
| Alekinha      | ALE          | 8                   | 0.40        | 0           |
| Kuybshevskaya | KUB          | 8                   | 0.40        | 0           |
| Olya          | OLY          | 8                   | 0.40        | 0           |
| Rikorda       | RIK          | 8                   | 0.40        | 0           |
| Kompaniskii   | KOM          | 6                   | 0.19        | 1           |
| Chirpoi       | CHI          | 4                   | 0.16        | 0           |
| Drobnye       | DRO          | 4                   | 0.16        | 0           |
| Ainu Bay      | AIB          | 0                   | 0.00        | 0           |
| Ainu Creek    | AIC          | 0                   | 0.00        | 0           |
| Rasshua       | RAS          | 0                   | 0.00        | 0           |
| Sernovodskoe  | SER          | 0                   | 0.00        | 0           |
| Zapadnaya     | ZAP          | 0                   | 0.00        | 0           |
| Okhotsk       |              |                     |             |             |
| Ekarma        | EKA          | 14                  | 0.42        | 16          |
| Tokotan       | TOK          | 14                  | 0.42        | 16          |
| Berzovka      | BER          | 12                  | 0.38        | 16          |
| Kompaniskii   | KOM          | 10                  | 0.37        | 0           |
| Olya          | OLY          | 10                  | 0.37        | 0           |
| Vodopadnaya   | VOD          | 10                  | 0.37        | 0           |
| Drobnye       | DRO          | 8                   | 0.20        | 4           |
| Ainu Creek    | AIC          | 4                   | 0.12        | 0           |
| Baikova       | BAI          | 4                   | 0.12        | 0           |
| Alekinha      | ALE          | 2                   | 0.07        | 0           |
| Ainu Bay      | AIB          | 0                   | 0.00        | 0           |
| Bolshoy       | BOL          | 0                   | 0.00        | 0           |
| Chrinkotan    | CHR          | 0                   | 0.00        | 0           |
| Lake Lazoumye | LAL          | 0                   | 0.00        | 0           |
| Rasshua       | RAS          | 0                   | 0.00        | 0           |
| Ryponkicha    | RYP          | 0                   | 0.00        | 0           |
| Zapadnaya     | ZAP          | 0                   | 0.00        | 0           |

particular, eigenvector centrality correlations of the Epi-Jomon network demonstrate the sharpest decline moving from a 0.975 average correlation with the removal of a single node to a 0.872 average correlation with the removal of five nodes and a dramatic increase in the spread of correlation values (see mean and standard deviations in Table 3). The more severe decline of eigenvector correlations is not surprising as eigenvector centrality is calculated based upon the dependence of a node's centrality in



**Fig. 4** Average correlation of centrality measures between actual and sampled data for Epi-Jomon and Okhotsk networks

the network and can therefore fluctuate with the omission of only a few nodes (Costenbader and Valente 2003). Perhaps most unusual are the differences in correlation means associated with betweenness centrality with the Epi-Jomon network showing stable and high correlation values and the Okhotsk network demonstrating significantly greater variation (Table 3). This pattern is likely a product of the highly skewed betweenness centrality values of the Epi-Jomon network with only one site (BER) demonstrating strong betweenness centrality as compared to a more balanced Okhotsk network with three sites characterized by high betweenness centrality. Because of this distribution, it is more likely that in the random sampling of the Epi-Jomon network, nodes with no influence on betweenness centrality were removed in each sample, whereas in the Okhotsk network, there is a greater probability that nodes with higher betweenness centrality were removed.

In general, the greater instability of centrality scores in the smaller Epi-Jomon network suggests that interpretations based on the Epi-Jomon network are only

**Table 3** Mean correlation values and standard deviations of centrality measures between actual and sampled data for Epi-Jomon and Okhotsk networks

| Number of removed nodes | Degree |       | Eigenvector |       | Betweenness |       |
|-------------------------|--------|-------|-------------|-------|-------------|-------|
|                         | Mean   | SD    | Mean        | SD    | Mean        | SD    |
| Epi-Jomon               |        |       |             |       |             |       |
| 1                       | 0.989  | 0.006 | 0.975       | 0.023 | 0.999       | 0     |
| 2                       | 0.984  | 0.015 | 0.952       | 0.044 | 0.999       | 0     |
| 3                       | 0.972  | 0.031 | 0.921       | 0.118 | 0.999       | 0     |
| 4                       | 0.957  | 0.052 | 0.889       | 0.183 | 0.999       | 0.011 |
| 5                       | 0.934  | 0.084 | 0.872       | 0.22  | 0.999       | 0.027 |
| Okhotsk                 |        |       |             |       |             |       |
| 1                       | 0.996  | 0.003 | 0.996       | 0.004 | 0.935       | 0.085 |
| 2                       | 0.992  | 0.006 | 0.991       | 0.011 | 0.902       | 0.107 |
| 3                       | 0.987  | 0.011 | 0.984       | 0.021 | 0.888       | 0.116 |
| 4                       | 0.98   | 0.018 | 0.977       | 0.031 | 0.855       | 0.148 |
| 5                       | 0.973  | 0.025 | 0.967       | 0.064 | 0.863       | 0.145 |

informative if the unknown “true” network (which would include the entire “real” population) is thought to be similar in size and density. In other words, if the archaeologically constructed network size is thought to differ by only a few nodes or ties (3 or less), then centrality scores from the constructed network can be reliably used for interpretation of the broader, unknown network. For the Okhotsk network, the strong stability of degree and eigenvector centrality scores throughout all sampling intervals suggests that the constructed network and the “true” network do not have to be as similar as the more unstable Epi-Jomon network. Therefore, it is likely that the constructed Okhotsk network provides centrality scores that can be interpreted as representative of the “true” network, with the caveat that previous archaeological research has not drastically overlooked or misinterpreted Okhotsk period archaeological sites.

Once the stability of centrality scores is established for all networks under analysis, it is recommended to identify which individual nodes contribute most significantly to changes in graph-level measurements. For example, in this research, network ties are constructed through inferring the movement of pottery samples from one archaeological site to another archaeological site using elemental characterization methods. As is typical in many archaeological datasets, some archaeological sites within the Kuril archipelago have significantly greater and more diverse artifact assemblages with the consequence that some archaeological sites may demonstrate stronger relationships to other sites due to repeated pottery movement. The basic assumption here is that more prominent nodes with stronger ties are more meaningful to the structure and interpretation of the archaeological network. However, what remains less well understood in sparse networks is the influence of less prominent nodes with weak network ties, defined here as nodes and ties with lower degree and non-repeating connections.

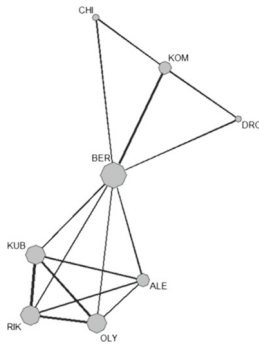
In order to address the influence of strong and weak nodes on network structure, a valued matrix was constructed for both the Epi-Jomon and Okhotsk datasets. In contrast to the previously analyzed binary matrices used for bootstrap analysis, the valued matrices included the total number of times that pottery samples from one site

were geochemically associated with pottery from another archaeological site or geologic location. Self-ties are not reported in this research as a majority of pottery samples (~60 %) demonstrate no movement between archaeological sites. Once valued matrices were constructed, sensitivity analysis proceeded by removing a single node and its associated ties from the network and re-calculating graph-level indices (GLIs) including graph density and graph centralization based upon degree, eigenvector, and betweenness centrality. In slight contrast to node-level centrality, graph centralization measures the tendency for any single point to be more central than all other points in the network (Freeman 1979). Centralization measures are calculated by summing the total differences between individual actor centralities and the maximum actor centrality (numerator) divided by the theoretical maximum possible difference of centrality within the network (denominator) (Freeman 1979; Wasserman and Faust 1994). This calculation produces a standardized network centralization score between zero and one with values closest to one representing a more centralized network graph and values closest to zero representing a less centralized graph.

Results of the sensitivity analysis (see Fig. 5) generally conform to initial predictions that archaeological sites with higher degree values demonstrate a stronger influence on graph-level indices. For example, the site of Berezovka (BER) is a highly central and well-connected site in the Epi-Jomon network, and removal of the site produces significant changes in graph density and centralization values for degree, eigenvector, and betweenness. Perhaps most important to this research is the result that less prominent or lower degree archaeological sites do not appear to significantly influence graph density or centralization when removed. In general, both graphs demonstrate that except for the sites with the highest degree, removal of any single node and their ties does not significantly alter graph-level indices.

In summary, the construction of networks from hunter-gatherer archaeological data can often be considered an extreme example of aggregation and fragmentation. Common examples of this include the aggregation of social ties over centuries or millennia and the fragmentation of material cultural data that can limit analysis to only a handful of archaeological sites. While exploratory, it has been demonstrated here that the tools exist within network analysis methods to evaluate the stability of sparse networks constructed from hunter-gatherer archaeological data. Specifically, this includes promoting the use of longitudinal networks, the use of bootstrap simulation to evaluate the stability of node centralities, and sensitivity analysis to assess the influence of strong and weak nodes on the overall structure of the network. Results from these methods suggest that while archaeological data is far from perfect, minor variations surrounding network size or nodal attributes are largely insignificant in the interpretation of the overall network graph. In other words, as long as archaeologists provide datasets that produce a reasonable network model, then the lack of information concerning one or two nodes (or even five nodes) does not significantly alter basic network measurements. Furthermore, using the methodologies described above, archaeologists can also empirically evaluate which centrality measures are most robust for their set of data rather than blindly applying and interpreting any or all of the centrality measures available. Overall, network analysis of hunter-gatherer archaeological data will rarely be able to provide the level of detail associated with social science research of modern populations, but it is evident from this research that networks





Epi-Jomon (2500-1300 cal BP) – Valued Network  
 Graph Density: 0.243  
 Centralization (Degree): 0.500  
 Centralization (Eigenvector): 0.295  
 Centralization (Betweenness): 0.189

(Width of line indicates strength of relationship;  
 isolates removed from display)

### Epi-Jomon

Change in graph level indices with node removed

| Removed Node /Site | Site Abbrev. | Degree (Valued) | Graph Density | Centralization (degree) | Centralization (Eigenvector) | Centralization (Betweenness) |
|--------------------|--------------|-----------------|---------------|-------------------------|------------------------------|------------------------------|
| Berezovka          | BER          | 16              | Medium        | High                    | High                         | High                         |
| Kuybshvskaya       | KUB          | 12              | Medium        | Low                     | Medium                       | Low                          |
| Olya               | OLY          | 12              | Medium        | Low                     | Medium                       | Low                          |
| Rikorda            | RIK          | 12              | Medium        | Low                     | Medium                       | Low                          |
| Alekinha           | ALE          | 8               | Low           | Low                     | Low                          | Low                          |
| Kompaniskii        | KOM          | 8               | Low           | Medium                  | Low                          | Low                          |
| Chirpoi            | CHI          | 4               | Low           | Low                     | Low                          | Low                          |
| Drobnye            | DRO          | 4               | Low           | Low                     | Low                          | Low                          |
| Ainu Bay           | AIB          | 0               | Medium        | Low                     | Low                          | Low                          |
| Ainu Creek         | AIC          | 0               | Medium        | Low                     | Low                          | Low                          |
| Rasshua            | RAS          | 0               | Medium        | Low                     | Low                          | Low                          |
| Sernovodskoe       | SER          | 0               | Medium        | Low                     | Low                          | Low                          |
| Zapadnaya          | ZAP          | 0               | Medium        | Low                     | Low                          | Low                          |

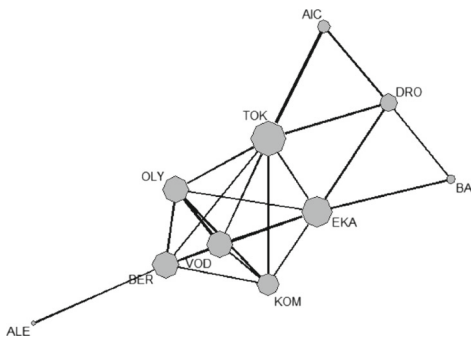
High: >2 standard deviation (SD) change; Medium: >1 and <2 SD change; Low <1 SD change

**Fig. 5** Visualization of Epi-Jomon and Okhotsk valued network graphs and results of sensitivity analysis (*width* of line indicates strength of relationship; isolates removed from display)

constructed from archaeological data can still provide statistically robust models with which to build interpretations of the past.

### Using Network Form to Explore Network Function

As previously discussed, social networks within hunter-gatherer societies likely function in multiple roles including, but not limited to, facilitating the exchange of social and environmental information, the trade of materials and/or resources, the maintenance of friendships, and/or the development political alliances. Furthermore, in many small-scale archaeological contexts, it is difficult to know the exact type of social relationship that might be represented by the material remains under examination. However, it is argued here that by building a statistically robust network structure that can highlight key network characteristics, the “infinite” range of network functions can



Okhotsk (1300-700 cal BP) – Valued Network  
 Graph Density: 0.176  
 Centralization (Degree): 0.367  
 Centralization (Eigenvector): 0.276  
 Centralization (Betweenness): 0.057

(Width of line indicates strength of relationship; isolates removed from display)

Okhotsk

Change in graph level indices with node removed

| Removed Node/Site | Site Abbrev. | Degree (Valued) | Graph Density | Centralization (Degree) | Centralization (Eigenvector) | Centralization (Betweenness) |
|-------------------|--------------|-----------------|---------------|-------------------------|------------------------------|------------------------------|
| Tokotan           | TOK          | 16              | Medium        | High                    | Medium                       | High                         |
| Ekarma            | EKA          | 14              | Medium        | Low                     | Medium                       | High                         |
| Berezovka         | BER          | 12              | Medium        | Low                     | Medium                       | Low                          |
| Olya              | OLY          | 12              | Medium        | Low                     | High                         | Low                          |
| Vodopadnaya       | VOD          | 12              | Medium        | Low                     | High                         | Low                          |
| Kompaniskii       | KOM          | 10              | Low           | Low                     | Medium                       | Low                          |
| Drobnye           | DRO          | 8               | Low           | Medium                  | Low                          | Low                          |
| Ainu Creek        | AIC          | 6               | Low           | Medium                  | Low                          | Low                          |
| Baikova           | BAI          | 4               | Low           | Medium                  | Low                          | Low                          |
| Alekinha          | ALE          | 2               | Low           | Medium                  | Low                          | Low                          |
| Ainu Bay          | AIB          | 0               | Low           | Low                     | Low                          | Low                          |
| Bolshoy           | BOL          | 0               | Low           | Low                     | Low                          | Low                          |
| Chrinkotan        | CHR          | 0               | Low           | Low                     | Low                          | Low                          |
| Lake Lazournye    | LAL          | 0               | Low           | Low                     | Low                          | Low                          |
| Rasshua           | RAS          | 0               | Low           | Low                     | Low                          | Low                          |
| Ryponkicha        | RYP          | 0               | Low           | Low                     | Low                          | Low                          |
| Zapdanaya         | ZAP          | 0               | Low           | Low                     | Low                          | Low                          |

High: >2 standard deviation (SD) change; Medium: >1 and <2 SD change; Low <1 SD change

Fig. 5 (continued)

be potentially narrowed to a group of network types that can be further examined by alternative forms of archaeological evidence.

Epi-Jomon

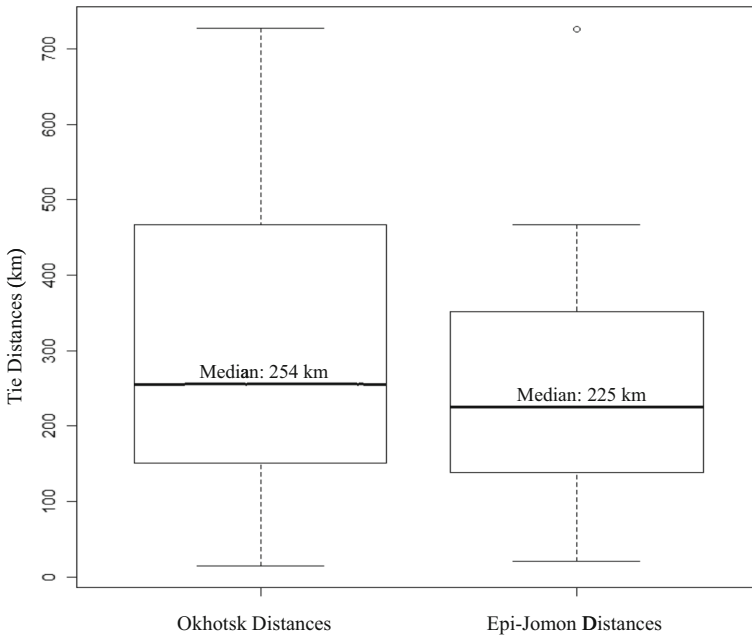
Based on the quantification of node-level and graph-level centrality measurements as well as the visualization of network form, the Epi-Jomon and Okhotsk networks demonstrate a few unique characteristics useful in exploring network function. Perhaps most evident in the visualization and centrality measures of the Epi-Jomon network is the presence of a single node (Berezovka—BER) with a significantly higher betweenness centrality value and a unique location within the network graph. In classic social network analysis studies, such as the analysis of elite family networks in pre-Renaissance Italy (Padgett and Ansell 1993), nodes with high betweenness values are

often considered important social or regional hubs which serve to facilitate the exchange or redistribution of information or materials and may even exert a certain degree of power or influence over other nodes in the network. In addition, when the geographic location of a site is considered, an interesting pattern develops where sites located in the central region (DRO, CHI) are only indirectly connected to sites in the southern region through ties with the site of Berezovka. While preliminary, this information suggests that geography and mobility likely play an important role in the structuring of the Epi-Jomon network given that ties are generally between nearest neighbors and not between sites separated by significant geographic distances. Based upon this structural type, it can be initially hypothesized that the Epi-Jomon network may function as a semi-centralized redistribution system with populations in different archaeological sites accessing materials or information through indirect or down-the-line trade by maintaining connections with their nearest neighbors but not direct contact with distant partners. It is possible that this network type is also representative of seasonal mobility patterns with potters moving vessels between different locations or making pottery vessels in one central location and redistributing them across the landscape. Based upon differences in stylistic and technological pottery characteristics between different sites, this scenario is considered unlikely but will be examined in future archaeological research.

### Okhotsk

In the examination of Okhotsk network structure, key differences emerge in both the centrality of nodes and the geographic distribution of ties. Unlike the Epi-Jomon network, no single node stands out as highly centralized but rather a number of sites (EKA, TOK, BER, OLY, VOD) demonstrate degree centrality values over twice the average centrality of other network nodes. Furthermore, the distribution of ties within the Okhotsk network suggests an increase in the proportion of inter-regional connections with 50 % (11 of 22) of ties connecting sites located in different regions compared to only 26 % (4 of 15) of ties in the Epi-Jomon network. This pattern of longer distance ties can also be recognized in the distribution of tie lengths within both networks, with the Okhotsk network demonstrating a similar median tie distance but greater overall variability (see Fig. 6).

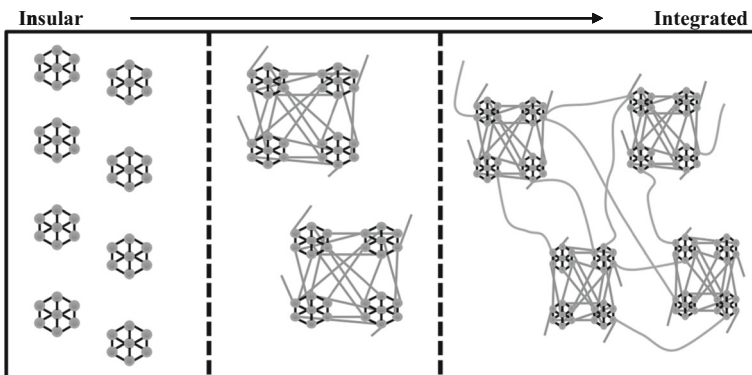
Building from predictions of the information networks model (Fitzhugh *et al.* 2011), lower graph centralization and increased variability in tie distances suggest that the Okhotsk network tends towards a more “integrated” network structure with ties occurring at the local, supra-local, and regional scales (see Fig. 7). In contrast, the Epi-Jomon network displays a tendency towards a more “insular” network with emphasis on ties at the local and supra-local scales. It is proposed here that the presence of ties at multiple spatial scales, particularly supra-local and inter-regional levels, indicates an attempt to reduce uncertainty associated with the local socio-natural environment by maintaining long-distance relationships. Based upon classical economic theory (Knight 1921), uncertainty refers to the incomplete knowledge concerning the result of any action or behavior, with the development and maintenance of social relations often considered a form of adaptive behavior for mitigating socio-natural uncertainty (Fitzhugh *et al.* 2011; Gjesfjeld and Phillips 2013; Hamilton *et al.* 2007; Kelly 1995; Minc 1986; Minc and Smith 1989; Moore 1981; Rautman 1993; Whallon 2006). In theory, consistently reproduced social ties at multiple spatial scales help reduce uncertainty by providing diverse opportunities to acquire knowledge of social



**Fig. 6** Boxplot of Okhotsk and Epi-Jomon tie distance

and natural conditions by establishing formal partners outside of an individual’s local area. In many small-scale societies, such social relationships can be viewed as a prerequisite for colonization and long-term habitation in isolated or unpredictable habitats as they enable a form of adaptive flexibility to mitigate the variable outcomes of diverse hazard events (Fitzhugh 2004; Fitzhugh *et al.* 2011). Based upon this theory, it is perhaps not surprising that 65 % of archaeological sites with evidence for Okhotsk occupation are found in the more remote central and northern regions of the island chain.

Overall, preliminary analysis of network function within the Okhotsk network, as derived from network form, suggests a potentially risk-reducing role of social relationships that promote the direct exchange of material and information over a large range of spatial scales. Perhaps most interesting is the suggestion that populations in more



**Fig. 7** Graphical representation of various network structures (adapted from Fitzhugh *et al.* 2011)

uncertain and vulnerable socio-natural environments, such as the Okhotsk populations in the remote Kuril Islands, value the acquisition of information and materials enough to accept the greater risk and increased costs associated with maintaining connections at supra-local and inter-regional spatial scales. While numerous factors influence the development and maintenance of long-distance social relationships in the region (group mobility, boating technology, socio-political relationships, emerging market economies), this research provides a range of starting hypotheses concerning the function of social networks with which future archaeological research in this region can examine.

## Conclusion

In a publication by Brughmans (2010: p. 1), the author emphasized caution in the “uncritical application of network analysis methods developed in other disciplines” with the “need for developing a specifically archaeological network analysis.” In order to fully realize an archaeological network analysis, it is important that both the theoretical and methodological challenges associated with archaeological data are evaluated. In this research, the methodological challenges of data aggregation and fragmentation are explored through data evaluation methods developed in social science research. Despite often providing extreme examples of aggregation and fragmentation, results using archaeological data from compositional analysis demonstrate that sparse archaeological networks are fairly stable over various network sizes and largely insensitive to the absence of weak nodes. While archaeologists can almost never fully identify the “true” function(s) or size of social networks in the past, it is argued here that by gaining confidence in the form of the archaeological network, it is possible to explore a range of interpretations that can help in understanding the complex relationships of individuals and societies in the past.

**Acknowledgments** I would like to thank two anonymous reviewers, Ben Fitzhugh, S. Colby Phillips, Tom Brughmans, Anna Collar, Fiona Coward, and Barbara Mills for the extremely helpful and insightful comments on earlier versions of this text. In addition, I would like to give a special thanks to Steve Goodreau for not only his comments but also his patience in helping me develop the ideas and statnet code for this paper. Funding support for the geochemical analysis of pottery artifacts was provided by a Doctoral Dissertation Improvement Grant from the National Science Foundation-Arctic Social Sciences division. Finally, I would like to thank all of the wonderful collaborators and participants from the Kuril Biocomplexity Project that have worked so hard on understanding one of the most unique and amazing regions of the world.

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