Supplemental Methods

Network Analysis

The incomplete nature of archaeological data holds significant challenges to the implementation of SNA methods for understanding the past (Brughmans, 2013; Mills, 2017; Peeples, 2017; Roberts et al., 2021). Various solutions have been proposed, but the common theme is the use of statistical validation to assess possible biases or errors in the data being analyzed (Östborn and Gerding, 2014; Peeples and Roberts, 2013). Östborn and Gerting (2014) discuss the need for statistical rigor in network analyses in archaeology, and advocate for a random permutation approach to randomly reshuffle data to evaluate observed patterns from randomly dispersed datasets.

Brughmans (2013) argues that there are two major problems with many recent implementations of SNA in archaeology: (1) a general unawareness of the history and diversity of formal network methods and their archaeological suitability has resulted in a very limited scope of SNA applications; and (2) most applications of SNA in archaeology are not driven by research questions, but rather a limited number of popular models and techniques. Brughmans (2013) suggests that framing studies of archaeological SNA applications using complex systems theory can help alleviate some of the limitations.

Central tenets of SNA are that: 1) Actors and their actions are viewed as interdependent; 2) Ties or linkages between actors are channels for the transfer of resources; 3) Network models view the network structural environment as providing opportunities for or constraints on individual action; and 4) Network models conceptualize structure (social, economic, political, and so forth) as lasting patterns of relations among actors (Brughmans, 2013; Wasserman and Faust, 1994).

Network Indices

We tested three commonly used comparative indices, including co-presence, Brainerd-Robinson (BR) similarity (Brainerd, 1951; Robinson, 1951), and chi-square distance. Co-presence is a simple similarity metric that establishes connections on the basis of the presence of particular categories of data at multiple sites (Brughmans, 2010). Following Peeples (2017), co-presence is calculated as:

$$P = A \times A^T$$

Where P is the number of overlapping categories between sites, A is the incidence matrix of categories, and A^T is the transposed matrix of those categories. We generated co-presence networks using a threshold of 50% similarity. This threshold was chosen based on trial-and-error, whereby 50% yielded the best results.

BR similarity calculates similarity between nodes as a proportion of the representation of the total number of categories present within the data. This is a commonly applied similarity metric, and is calculated, following Peeples (2017), using the equation:

$$S = \frac{2 - \sum c|x_c - y_c|}{2}$$

Where *S* is the BR similarity score, *c* represents all the categories of data, *x* is the proportion of *c* in the first data assemblage, *y* is the proportion of *c* in the second assemblage.

Lastly, Chi-Square distance is a measurement used for correspondence analyses that is weighted by the inverse of a data category's frequency (Dodge, 2008). Chi-square distance is calculated using the equation:

$$X_{nc} = \sqrt{\sum \frac{1}{a_n}(x_n - y_n)^2}$$

Where a_n is the proportional abundance of the *n*th element of the average row profile in the data, and *x* and *y* represent the row profiles for the two sites being compared. Chi-square distances are useful for accounting for rare attributes in the formation of data connections (Peeples and Roberts, 2013).

Assessment of sampling error on network results

To assess the effects that sampling error may have on our results, we calculated centrality metrics (degree, eigenvector, and betweenness) using 1000 bootstrap simulations to re-sample our data (following Mills et al. 2013; also see Roberts et al. 2021) and evaluate changes between randomized samples and our original dataset. Increased variability indicates higher risk of sampling error. Degree centrality for a node is defined as the total number of direct connections in which that node is involved (Peeples, 2017; Peeples and Roberts, 2013). Betweenness centrality is defined as the number of shortest paths between pairs of nodes in a network involving the target node divided by the total number of shortest paths in the network as a whole (Peeples, 2017; Peeples and Roberts, 2013). Eigenvector centrality is a measure of a node's importance in a network defined in relation to other nodes to which it is connected (Peeples, 2017; Peeples and Roberts, 2013; Roberts et al., 2021).

Next, we re-assess these networks for their resilience to sampling biases using 1000 bootstrap simulations to subsample the data into 10% intervals and calculate the rank-order correlation (Spearman's ρ) of the overall sample and each sub-sample (Costenbader and Valente, 2003; Peeples, 2017). We also assessed these biases using fewer numbers of simulations (100, 200, 500), and results remained largely identical. This allows us to evaluate the errors in the dataset that may arise from sampling issues (see Supplemental File). This procedure is performed to account for missing nodes and edges in the dataset, which often plague archaeological investigations.

Then, we assess the stability of individual nodes and edges in the network by using 1000 bootstrapped simulations of our network data to create sub-sampled datasets. This allows us to compare the original dataset with sub-sampled components for agreement or divergence.

Ceramic Chronologies

Relative chronologies for ceramics follow the typologies described in Douglass (2016). Based upon prior observations and studies (e.g., Douglass, 2016; Hixon et al., 2021; Parker Pearson, 2010; Wright et al., 1996), ceramics containing triangular punctation marks and incising were found among the oldest archaeological contexts, spanning from the 9th century AD to between the 13th and 16th centuries AD. Circular and square punctations appear slightly later (around the 11th century), and the latest decorative style is shell-combing, which becomes prevalent around the 18th – 20th centuries. Using these decorative characteristics, we constructed the relative chronology used in this analysis.

Paleoclimate Assessment using Bayesian Change Point Analysis (BCPA)

We use Bayesian change point analysis (BCPA; Erdman & Emerson 2007), following Hixon et al. (2021) to estimate general trends in climatological conditions from speleothem proxies collected by Faina et al. (Faina et al., 2021)(2021) in Asafora Cave, SW Madagascar. BCPA is a statistical modeling approach that uses Markov Chain simulation to identify splits in a sequence of datapoints that can be approximated reasonably with a single mean value. We conduct BCPA in *R* (v. 4.1.2; R Core Team, 2021) using the *bcp* package (Erdman and Emerson, 2008).

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