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Archaeological networks, community detection, and critical scales of interaction in the U.S. Southwest/Mexican Northwest

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ABSTRACT

Archaeologists have long recognized that spatial relationships are an important influence on and driver of all manner of social processes at scales from the local to the continental. Recent research in the realm of complex networks focused on community detection in human and animal networks suggests that there may be certain critical scales at which spatial interactions can be partitioned, allowing researchers to draw potential boundaries for interaction that provide insights into a variety of social phenomena. Thus far, this research has been focused on short time scales and has not explored the legacies of historic relationships on the evolution of network communities and boundaries over the long-term. In this study, we examine networks based on material cultural similarity drawing on a large settlement and material culture database from the U.S. Southwest/Mexican Northwest (ca. 1000–1450 CE) divided into a series of short temporal intervals. With these temporally sequenced networks we: 1) demonstrate the utility of network community detection for partitioning interactions in geographic space, 2) identify key transitions in the geographic scales of network communities, and 3) illustrate the role of previous network configurations in the evolution of network communities and their spatial boundaries through time.

1. Introduction

General network thinking and relational perspectives have a long history in archaeology, but it is only recently that we have seen a dramatic increase in the frequency of empirical work explicitly using formal network analytical tools to explore archaeological questions (see discussions in Brughmans and Peeples 2017; Peeples 2019; Mills 2017). The most popular network approaches in archaeology in recent years have included both explicitly spatial networks where connections are assessed in terms of the distances, paths, or travel costs among features often using GIS tools (e.g., Broodbank 2000; Menze and Ur 2012; Rivers et al. 2013; Verhagen et al. 2013, 2019; Wernke 2012) as well as non-spatial networks where connections are assessed in terms of the presence/absence, frequency, or similarities in material culture (e.g., Birch and Hart 2018; Blake 2013, 2014; Buchannan et al. 2019; Coward, 2013; Golitko and Feinman, 2015; Mills et al., 2013a; Mizoguchi, 2013; Peeples, 2018; Mills et al., 2013b, etc.). In the latter group, interactions are defined and assessed without direct reference to the relative or absolute spatial configurations of nodes though spatial relationships are sometimes assessed after the networks have been generated (see Buchanan et al., 2019; Golitko et al., 2012; Golitko and Feinman, 2015; Gravel-Miguel, 2016; Hill et al., 2015; Lulewicz, 2019; Mills et al., 2013a, 2013b, 2015). Indeed, one of the most robust patterns that has emerged from such considerations of material culture networks embedded in space is the frequent close relationship between likely vectors of interaction and spatial distance (Brughmans and Peeples 2023:Chapter 7). It is perhaps not surprising that social networks and spatial distance are often closely related, but the varied nature and strength of this relationship in different contexts and data sets suggests that this is a topic ripe for further study.

The relationship between formal networks of interaction and space has been a topic of great concern in the broader world of network science across geography, ecology, physics and other fields in recent years. Work addressing such issues is quite diverse, but there is a growing body of work that illustrates how social interactions of all kinds in human and animal networks can be influenced by spatial configurations and further that certain kinds of interactions tend to be concentrated within specific geographic ranges (Alessandretti et al. 2018; Balsa-Barreiro et al 2022; Barbosa et al. 2021; Glückler et al. 2017; Hamedmoghadam et al. 2019; Fletcher et al. 2013; Leng et al. 2021; Menezes and Roth 2017). For

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example, Fletcher and colleagues (2013) present an analysis of modularity, or the tendency of networks to be decomposed into smaller sub-groups, in animal movement networks derived from recapture and population genetic data for several species. Through this work they were able to identify statistically significant partitions of networks of movement and gene flow that were larger than the individual ranges of animals but smaller than the landscape scale of the species distributions. This suggests that there are key *meso*-scale partitions of certain animal populations that may represent fundamental scales for activities like mate selection that have been given substantially less attention than they warrant. In another recent study, Menezes and Roth (2017) explored geotagged social media content to identify natural scales of human movement based on a network connecting locations with shared check-ins or tagged images by multiple users. They found that study areas ranging in size from cities up to entire countries were marked by a small number of break points where slightly changing the radius of movement that they considered dramatically altered the detectable sub-divisions in that network. Further, they show that networks from the local to regional were decomposable into distinct geographic partitions at remarkably similar geographic scales.

Both of the studies briefly described above illustrate that the relationship between interaction and space is not always gradual but may be marked by major junctures, where small changes in spatial scale result in dramatic differences in network properties. Such *critical scales* are often interpreted as the scales at which key processes of interaction change, with different kinds or intensities of interaction occurring on either side of the transition. Critical scales for interaction are of great importance for tracking and modeling network behavior but are often difficult to directly identify without formal data for tracing interactions and/or mobility across broad geographic scales that cover several orders of magnitude in distance (see Fletcher et al. 2013; Hamedmoghadam et al. 2019; Keitt et al. 1997; Menezes and Roth 2017). Recent work in the realm of complex network science has attempted to address the issue of identifying such *critical scales* using network community detection methods (Menezes and Roth 2017). Specifically, algorithms for defining partitions or sub-groups within networks that are not based on spatial information can be applied and then any spatial patterns that exist in the sub-group structure can be assessed to determine whether patterns of interaction are tied to specific geographic scales. Such work has proven useful in decomposing large networks into sub-groups in a variety of settings but, as of yet, such work has been focused on single periods of measurement and has not tracked change through time or the legacies of network configurations.

The approach to identifying and assessing critical scales in networks has some general commonalities with the ways archaeologists have often discussed interactions embedded in space. Archaeologists have certainly long recognized that different kinds of interactions and mobility are likely to be organized around different geographic scales. It is common for archaeologists to draw on ethnographic or experimental information to model the most likely zones of certain types of behavior or mobility. For example, observations of Kofyar farmers in the Sahel of Nigeria (Stone 1991, 1992; see also Marchetti 1994 for another example) illustrate that in agricultural communities in this semi-arid environment the maximal distance that farmers typically travel for intensive agricultural activities is about two kilometers. This observation agrees well with archaeological observations in the U.S. Southwest of archaeological evidence of field locations in relation to settlements perhaps suggesting this observation can be generalized to a degree (see Adler et al., 1994; Varien et al. 2000). Indeed, distance thresholds based on this and similar work have proven useful in modelling settlement distributions in many regions (Kaše et al. 2022; Kruse 2007; Varien 1999). Similarly, drawing on a broad array of ethnographic and archaeological examples Arnold, Heidke, and others (Arnold, 1988; Arnold et al., 1991; Heidke et al. 2007) have argued that the distances that potters travel for resources fall off sharply from residences and most potters stay within about seven kilometers of their residences when gathering clay and other resources for pottery production. Drennan (1984) modeled the potential for the long-distance movement of goods across highland Mesoamerica based on his and others experiences and calculations of caloric requirements for overland travel with goods, suggesting that a burdened traveler can travel about 36 km in a day. This observation has frequently been used to model the potential for movement of goods and people in archaeological case studies in the U.S. Southwest (Hill et al. 2004; Wilcox et al. 2007; Wilcox 1996). Although the degree to which they are universal or even broadly generalizable is certainly an open question, such thresholds are useful as they help to put real-world limits on the kinds of movements and interactions we might expect within specific spatial frames. In most cases, however, such thresholds or *critical scales* are defined based on one particular ethnographic setting or body of comparative data and then applied to other areas without direct assessment. Further, such thresholds are often limited to the scales at which ethnographic and ethnoarchaeological research have been conducted, which is frequently small relatively to regional scales of archaeological analysis. To address some of these specific issues, in this analysis, we assess the degree to which it might be possible to generate similar assessments of *critical scales* of interaction from the ground up by directly assessing changing patterns of interaction intensity in network data.

In this study, we adapt methods for defining and evaluating *critical scales* using assessments of network clustering (drawing in particular on work by Menezes and Roth [2017] for geotagged image data) and apply them to archaeological data from the U.S. Southwest and Mexican Northwest. The goals of this process include 1) determining whether there is any evidence for critical scales or natural geographic scales across which these interaction networks can be divided and whether we can identify those with archaeological ceramic similarity data, 2) determining the degree to which the scales of any divisions identified are similar across time and space, and 3) determining the degree to which boundaries between spatial divisions persist or change through time. By tracking such dynamics through time, we will further investigate the timing of changes in network community boundaries across our study area to see how past network configurations or divisions might have influenced those in subsequent intervals. As we draw on methods and tools from network research spanning several disciplines, terminology for referencing specific network properties and analyses can be difficult as similar terms are sometimes used to refer to different things. To help with this issue, we provide a brief glossary of some of the key terms and define exactly how we use them in the context of this article (Table 1).

Table 1
Network terminology used in this study.

Term	Definition
Modularity	A formal measure of the structure of networks characterizing the tendency toward division into sub-groups
Community	A sub-group of nodes that is densely connected internally.
Partition	A formal assignment of all nodes in a network into mutually exclusive sub-groups or communities
Community detection	A term used to refer to various algorithmic approaches to detecting and defining sub-group structure (communities) of a network. In this study we use the Louvain community detection algorithm.
Critical scale	A term referring to geographic/spatial scales associated with abrupt changes in network connectivity. In other words, critical scales are geographic scales where small changes in the scale considered result in dramatic changes in network properties.
Prototypical scale	Following Menezes and Roth (2018), the prototypical scale is the distance between a pair of identified critical scales that is is most similar to all other distances within the same sub-division.

2. The study area and the cyberSW database

For the purposes of this study, we focus on a large portion of the U.S. Southwest and Mexican Northwest including southern Utah and Colorado, along with Arizona, New Mexico, portions of Texas, as well as the Mexican states of Sonora and Chihuahua. Temporally, we focus on the interval from 1000 CE to 1450 CE, which encompasses the maximal extent of agricultural settlement across this region as well as a period of dramatic transformation in settlement distribution and location including the depopulation of portions of the study area and the development of new population centers in areas that were previously relatively sparsely occupied (see Hill et al. 2004; Doelle 2000). The geographic and physiographic diversity of this study area along with the major shifts in settlement through time make this an excellent context for tracking critical scales as we will be able to assess how scales of interaction change or persist in light of major shifts in settlement distribution as well as whether certain locations or physiographic features consistently drive the creation of persistent network boundaries or subdivisions.

The data used in this study come from the cyberSW project online database. The cyberSW.org platform is an online resource and collaboration tool focused on standardizing and sharing archaeological settlement and material culture data from the U.S. Southwest and Northern Mexico, ca. 800–1800 CE (Mills et al. 2020). The cyberSW platform includes tools that allow users to query, download, map, and analyze archaeological data from across the region directly in a web browser or on their own computer. The archaeological data included in the database were generated over more than a century by academic archaeological research and compliance projects and have been compiled and standardized by a team of specialists including archaeologists, geochemists, sociologists, computer scientists, physicists, data infrastructure specialists, and others collaborating over more than two decades across several projects; the Coalescent Communities project (Hill et al. 2004), the Southwest Social Networks Project (Mills et al. 2013a, 2013b, 2015; Peeples et al. 2016), and the Chaco Social Networks project (Mills et al. 2018). These data represent and immense amount of effort by the field as a whole and the compilation of these data involved collaboration with numerous cultural resource management firms, museums and repositories, individual researchers, tribal organizations, land managers, and others.

The current version of the cyberSW database includes information on more than 20,000 archaeological sites in the region including a large number of sites with systematic counts of ceramic materials identified to standardized ware and type designations. In this study, we use data from a set of 1,790 settlements across the study area dating between 1000 and 1450 CE. The settlements selected are limited to those with at least 10

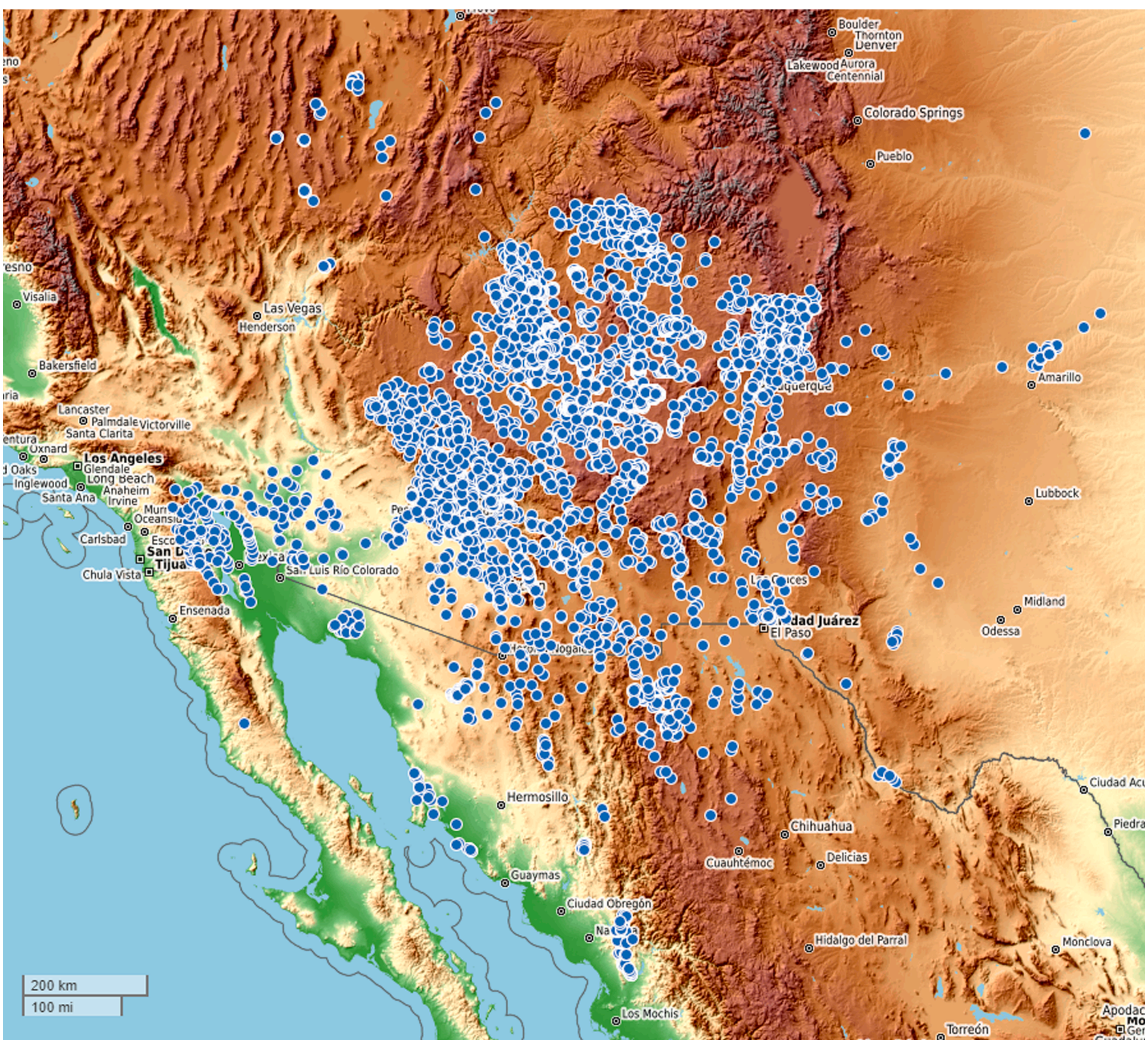

Fig. 1. Map showing the locations of all archaeological settlements in the cyberSW online database as of January 2023.

rooms and 30 systematically identified painted ceramic sherds (see Mills et al. 2013: Supplemental Materials for a discussion of the selection of sample size cut offs). These ceramic data are attributed to more than 1,100 ceramic type designations representing nearly ten million ceramic objects (see Fig. 1). In addition to the systematic ceramic counts we also use settlement location information (although those data are not available on the publicly accessible cyberSW.org platform due to concerns for site protection) as well as chronological and settlement size data from previous publications and observations. The expansive geographic scope and density of data available for this analysis meets the criteria for identifying critical scales of providing information on interaction across several orders of magnitude in distance and provides an excellent context for exploring issues of scale and evaluating whether there are critical scales marking changes in the relationships among these settlements and through time.

3. Generating network representations from archaeological data

In this study, we build on methods developed across several past regional scale archaeological network studies in the cyberSW study area (e.g., Borck et al. 2015; Mills et al. 2013a, 2013b, 2015, 2018; Peeples and Haas 2013; Peeples et al. 2016, etc.) to generate empirical networks of ceramic similarity for distinct 50-year intervals. We have chosen 50-year intervals as that corresponds with the typical chronological resolution of ceramic date ranges in our study area and represents essentially-two human generations. As the analyses presented here are complex and involve many steps applied to many different sub-divisions of the data, we have created a flow chart to help describe the analytical steps and the relationships among them (Fig. 2).

Since we are interested in change through time, we must first define the relevant chronological periods for each site and apportion the ceramic materials into the appropriate temporal intervals. In this study we rely on an empirical Bayesian approach for modelling site occupation spans known as "Uniform Probability Density Analysis" which was first developed by Ortman (2016) and later applied to archaeological ceramic network data by Mills and colleagues (2018). This approach, which is similar in many ways to approaches to generating summed probability distributions from radiocarbon data (e.g., Bird et al. 2022; Shennan et al. 2013), entails combining information on the chronological ranges associated with specific ceramic types with type frequency data to generate a model of the probability that a site was occupied or that a sherd was deposited in any given year. Briefly, every ceramic type present at a site is modeled using a uniform distribution representing the production dates for that type in the literature and then each distribution is multiplied by the frequency of that type in the assemblage. Data across all types are then summed to generate a composite *prior* distribution. In addition to this a modified *conditional* distribution is then calculated which models the overlaps among type dates for multiple types to estimate the most likely interval of deposition for each type (assuming that intervals when multiple types were present are more likely than intervals when just a single type was present). The *prior* and *conditional* distributions are finally multiplied to create a *posterior* distribution which accounts for both the original uniform distribution and the conditional model which prioritizes overlaps in date ranges for each

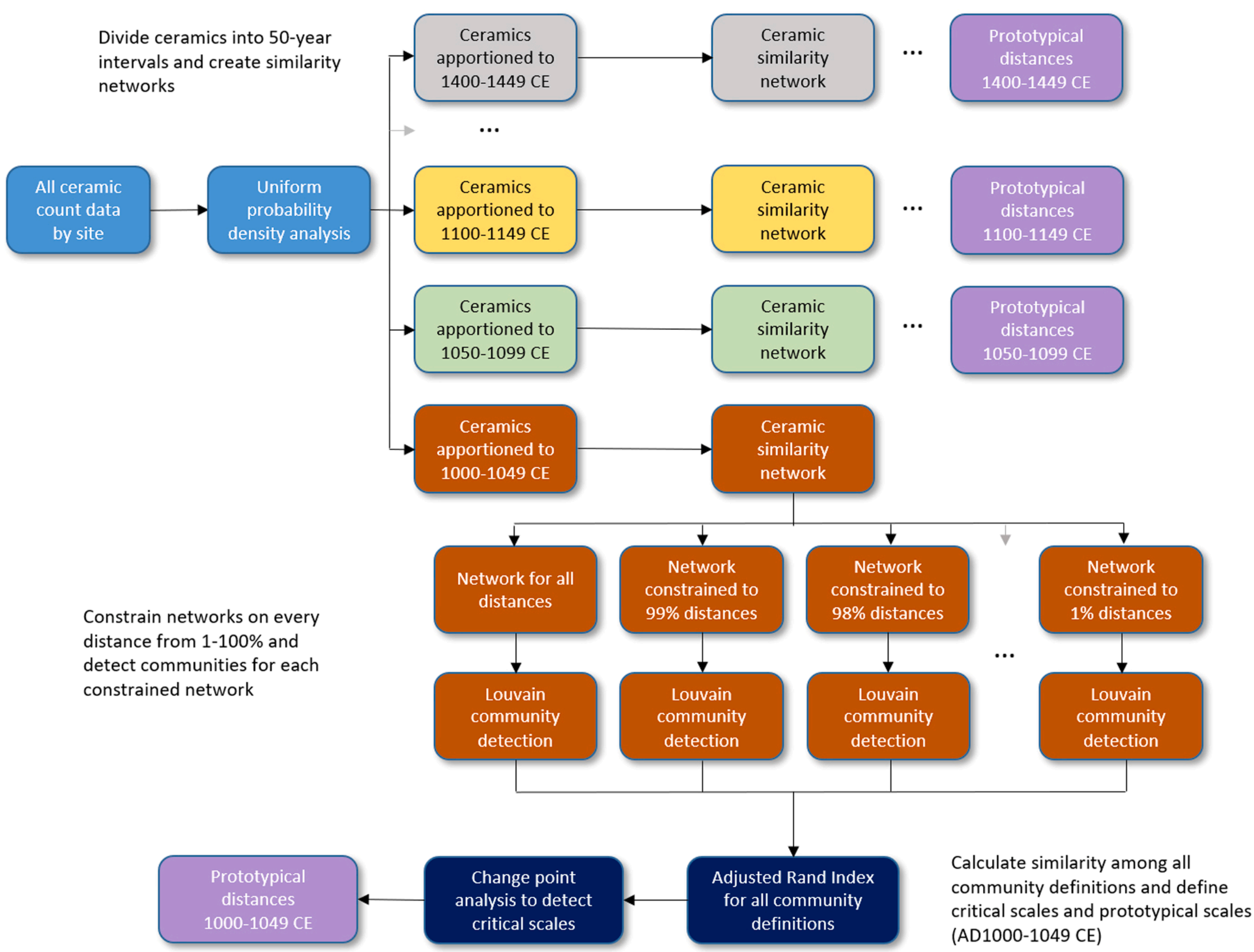

Fig. 2. Flow chart of analytical procedures for the analyses presented here.

type. This approach has been shown to generate dates shorter than the maximal possible range based on ceramic assemblages, to help eliminate minor secondary occupations, and to produce probability distributions that conform well to absolute dates where available (see Ortman 2016; Mills et al. 2018). The resulting *posterior* distribution for each type at each site provides estimates of the probability of deposition for every year a site was occupied so the estimated ceramic assemblages for a given interval can be generated simply by summing the relevant years in the *posterior* distribution for the interval desired. For this study, we divided our ceramic sample for each site into 50-year intervals between 1000 and 1449 CE (1000–1049 CE, 1050–1099 CE, etc.). The R code (R Core Team 2022) and data used to generate these temporal intervals and all other analyses in this article are provided in the supplemental materials.

After the procedure above we are left with discrete ceramic frequency datasets for each 50-year interval. To generate network models based on these data we define each individual settlement occupied in each interval as a node and then assess the presence and strength of edges between pairs of nodes in terms of the similarities in the proportional representation of ceramic wares present at those sites. Wares in the US Southwest/Mexican Northwest are broad categories of ceramics defined in terms of ceramic technology and materials (e.g., temper, paint types, etc.) that combine multiple temporally sequenced ceramic types which typically vary in terms of design style and other specific details. Wares are general categories that can often be attributed to broad regions of production and are relatively easy to identify and thus provide a good means for assessing the general degree of overlap in assemblages among sites. Similarities in ceramic assemblages are likely generated through an array of processes including exchange, the transmission of production practices, population movement, emulation, and shared expressions of social group membership or boundaries (e.g., Mills and Crown 1995; Stark 1998; Mills et al. 2016). Although we cannot typically be sure *which* of these processes (or others) are responsible for similarities in ceramic assemblages at macroregional scales, such similarities likely capture some of the most important social relationships among sites and broader regions across our study area (see Mills et al. 2016). In general, we interpret similarities in ceramic assemblages among pairs of sites as indicative of *probabilities* of interaction rather than direct interaction in a strict sense.

To assess similarities among pairs of sites we use a modified and rescaled version of the Brainerd-Robinson (Brainerd 1951; Robinson 1951) measure of similarity. This measure defines the similarity S between a pair of sites a and b as:

$$S = \frac{2 - \sum_k |p_{ak} - p_{bk}|}{2}$$

where k represents all ceramic wares, p_{ak} and p_{bk} represent the proportions of ware k at site a and b respectively. This version of the measure is scaled to range between 0 (indicating no similarity) and 1 (indicating perfect similarity) and we argue it provides a measure of the likely *strength* of connection between pairs of sites. Although in some past studies (e.g., Mills et al. 2013a, 2013b, 2015, 2018) these continuous similarity data have been reclassified into binary present/absent network ties for the purposes of visualization, in this study we simply use the raw similarities among every pair of sites as the weight of the ties between them (see also Peeples and Roberts 2013 for further explanations of such weighted similarity networks). In network terms, thus, we create an undirected weighted network of similarity for each 50-year interval.

We are further interested in evaluating the presence of detectable communities or sub-group structures within our weighted similarity networks. In order to do this, we use the Louvain method for community detection (Blondel et al. 2008) which is an algorithmic method for clustering nodes based on the optimization of network modularity based on the relative weight and density of connections within and between communities (see also Girvan and Newman 2002; Newman and Girvan 2004; Newman 2006 for related modularity-based approaches). The Louvain approach iteratively evaluates the density and strength of connections within a given community assignment compared to a random network to find the optimal partition of that network. The Louvain method is well-suited to the data used here as it can be applied to weighted networks and because it does not require that the analyst define the number of communities to be generated beforehand but rather determines community memberships and number of sub-groups automatically. In the analyses described below, this Louvain approach will be used to identify network sub-groups across a range of geographic scales (using the *igraph* R package; Csardi and Nepusz 2006).

4. Identifying critical scales in ceramic similarity networks

To assess the presence of critical scales or junctures in the spatial scale of network communities in the ceramic similarity networks generated here we follow the procedures described by Menenzes and Roth (2017) for social media geospatial data, modifying these methods where necessary for our ceramic similarity network data. The basic premise of this approach is that, if there are any breaks in interaction at certain geographic distances in our network, we would expect to see big changes in the composition and/or scale of network communities defined across relatively small changes in the distance considered. In other words, we are asking whether there are any key distances where the strength and scale of interactions tend to change rapidly or if instead changes are simply gradual across a range of distances. In their previous study, Menenzes and Roth (2017) not only found that communities and interactions tended to vary considerably at different distances, but also that the distances at which such junctures tended to occur were remarkable similar across many different study areas. This perhaps suggests fundamental geographic scales of certain kinds of human social networks. We are interested in determining whether such *critical scales* are detectable in our ceramic similarity networks.

The first step in this approach involves applying the Louvain network community detection algorithm to our weighted similarity networks for each interval constrained by increasing percentiles of the overall geographic distances among sites. Specifically, we take the full weighted network of ceramic similarities for a given interval and define communities using the Louvain algorithm. The map on the left in Fig. 3 shows clusters defined based on the full weighted network across all distances. We then do the same Louvain community detection procedure considering only the 99 % geographically closest distances among pairs of sites, and then the 98 % percent closest and so on all the way down to the very short distance ties represented by the 1 % closest distances between pairs of sites. At every distance considered, we use the Louvain algorithm to define communities. Fig. 3 shows a small number of illustrative examples of the 100 percentile community definitions generated for this study for just one temporal interval. Note that as shorter and shorter distances are considered, the number of communities increases as the longest distance connections are removed from consideration. We complete this same set of procedures for each of the nine 50-year intervals between 1000 and 1449 CE. For each temporal interval we then have 100 different definitions of communities among nodes each based on a slightly different distance cut-off (at 1 % intervals). It is important to point out here that, although there is clearly a spatial character to many of the communities detected by the Louvain algorithm as we can see in Fig. 3, no spatial data were used to define these communities. This instead represents independent evidence of the close relationship between social interaction and spatial distance.

The next step in this analytical process is to evaluate evidence for transitions or break points in the community definitions created across different distances. Our goal is to identify critical scales in the distribution of similarities in partitions where small changes in the distance considered lead to big changes in community membership. To compare multiple partitions of the same set of nodes we use a metric called the

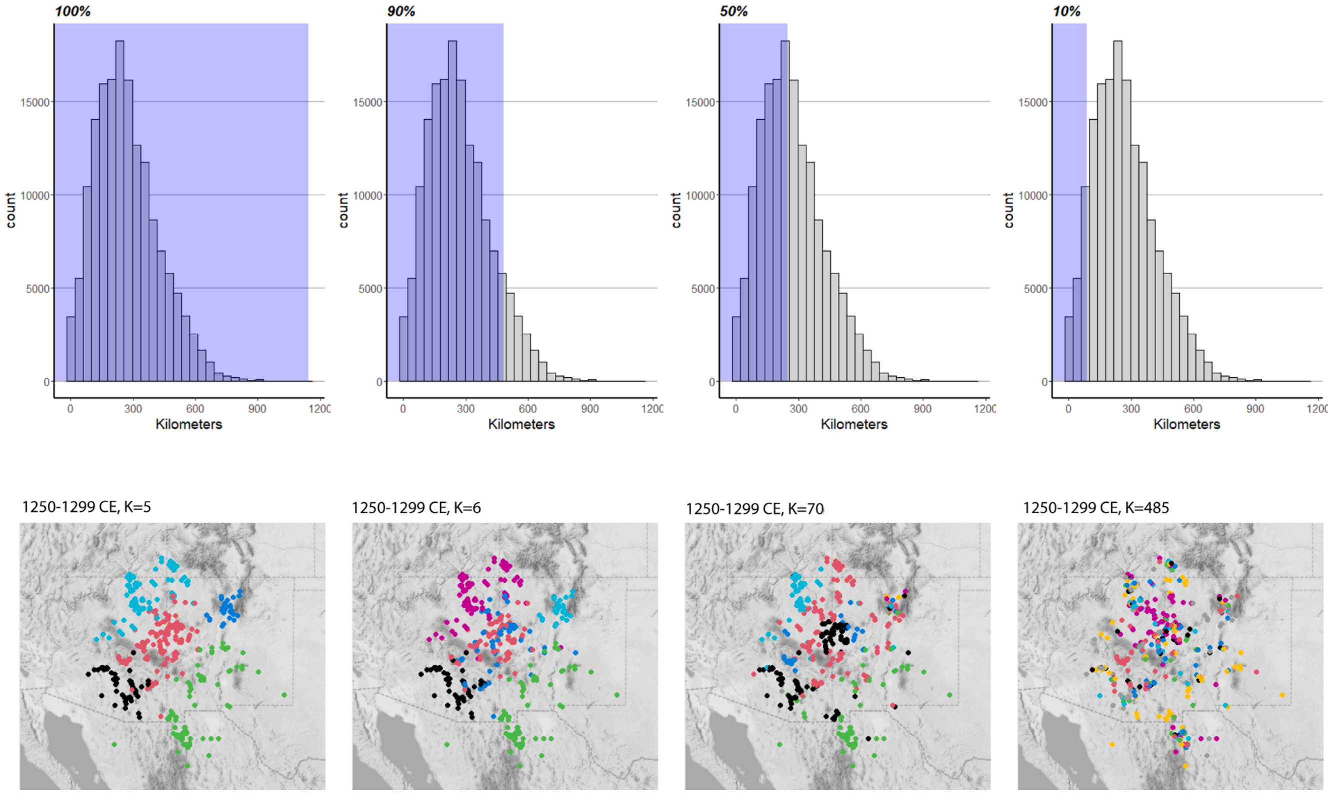

Fig. 3. Map of settlements in the 1250–1299 CE interval with community definitions considering different percentiles of distance (indicated by the associated histogram above each map). Nodes are color coded by community membership. Note that due to the large number of communities, colors are reused for multiple groups in the two maps on the right.

adjusted Rand Index (Gates and Ahn 2017; Rand 1971). This measure is frequently used to compare clustering results or partitions across multiple criteria or clustering methods (Hubert 1985) and is well-suited to the assessment we need here. The simple Rand Index between two partitions X and Y can be defined as:

$$R = \frac{a + b}{n(n-1)/2}$$

where a is the number of pairs of items that are in the same community in both partitions X and Y, b is the number of items that are in different communities in both X and Y and the denominator is the total count of pairs in the relationships considered. In other words, this measure is the ratio of the total number of agreements in partition assignment for pairs divided by the total number of possible pairs. The adjusted version of the Rand Index extends this procedure by accounting for the size and number of communities to compare the number of agreements observed to the number of agreements that could be expected by chance. This adjusted Rand Index will typically range from 0 to 1 where higher values indicate greater agreement between two sets of partitions but the value can also be negative if two partitions overlap less than would be expected in a random model. In this analysis we use the R implementation of the adjusted Rand Index in the *FreeSortR* package (Courcoux 2017).

Fig. 4 illustrates a heatmap which compares partitions at each of the 100 percentile distance cut-offs to all others using the adjusted Rand Index for one temporal interval. Looking at this plot there are clear discontinuities where small changes in percentile of distance lead to dramatic changes in partition agreement which is evidence in favor of the existence of critical scales across which networks of ceramic similarity operate. Following Menezes and Roth (2017), we define such critical scales using an adaptive energy agglomerative algorithm which iteratively finds the break points that maximize the within group similarity and between group dissimilarity (see Szekely and Rizzo, 2005;

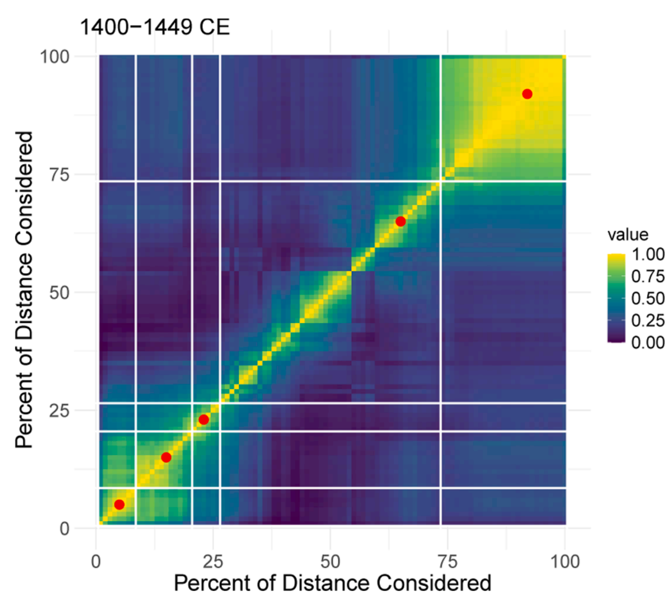

Fig. 4. A symmetric heat plot showing the adjusted Rand Index similarities among community partitions at distance percentiles from 1 to 100% for the 1400–1449 CE interval. White lines represent the critical scales (break points) between intervals and the red dots represent the prototypical distances for each sub-division.

Rizzo and Szekely, 2010; using the *ecp* R package; James and Matteson 2015). The details of this algorithm are beyond the scope of this article but in general this procedure iteratively finds optimal break points between clusters by merging adjacent segments of an ordered matrix (in this case ordered by the percent distance threshold) and assessing goodness-of-fit at each stage until merging no longer improves the fit. Discontinuities and break points were first identified within the entire range of adjusted Rand Index comparisons and then potential sub-divisions were assessed by running the same algorithm in the bottom quartile of distances to capture variation at a smaller scale. The lines dividing sets of relations in Fig. 4 represent the critical scales (break points) identified using this procedure for the interval represented.

Finally, we identify what Menezes and Roth (2017) call "prototypical" scales between each set of consecutive critical scales or break points. That is, the distance that is most similar to all other distances within a given sub-division. We interpret this as essentially the typical scale across which interactions focused across a given range operate (shown as red dots in Fig. 4). We conducted all of the analyses outlined above for each 50-year interval to allow us to compare results across periods and to determine whether there are any commonalities in break points and prototypical distances in ceramic similarity networks through time. With all of the procedures above we have identified the distances at which dramatic changes in interactions tend to occur as well as the distances that characterize typical interactions between those distances. Following Menezes and Roth (2017) we interpret these prototypical distances as the distances across which different kinds of interactions captured by our material culture similarity networks were concentrated.

5. Comparing distances and spatial boundaries

For all intervals analyzed in this study the methods outlined above generated between 5 and 7 spatial divisions that represent *prototypical distances* as we define them here. Fig. 5 shows boxplots of the prototypical distances for each partition from shortest to longest. Fig. 6 shows these same data with a line for each sequential prototypical distance within a given case and with time on the x-axis. In general, these two figures illustrate that, not only are there similar numbers of sub-divisions in each interval (at least for short to moderate distances) but the specific prototypical distances associated with these partitions are remarkably similar between periods, especially at shorter distances where the distributions are quite tight. This is particularly interesting because the study area saw major changes in settlement and regional scale population movements and even depopulation of substantial portions of the region during the interval considered here but we still see these similarities, at least at scales less than about 200 km. Thus, despite these major reconfigurations of settlement and regional population organization, interactions at short to moderate distances continued to operate at similar scales. Variability in longer distance ties is interesting but we argue is at least partially attributable to changes in the overall

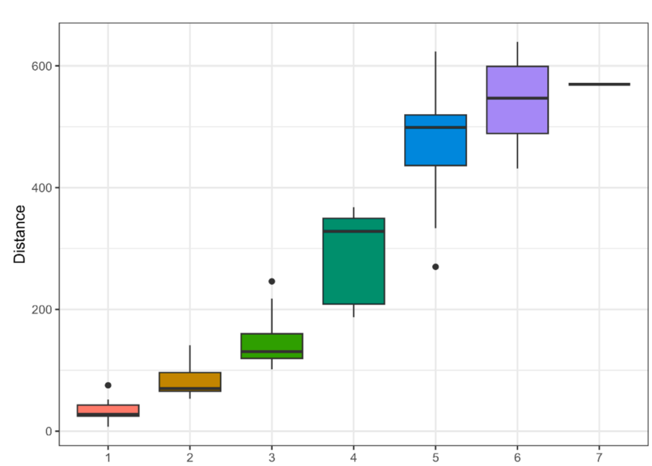

Fig. 5. Boxplot showing the distance in kilometers of sequential prototypical distances for all periods considered.

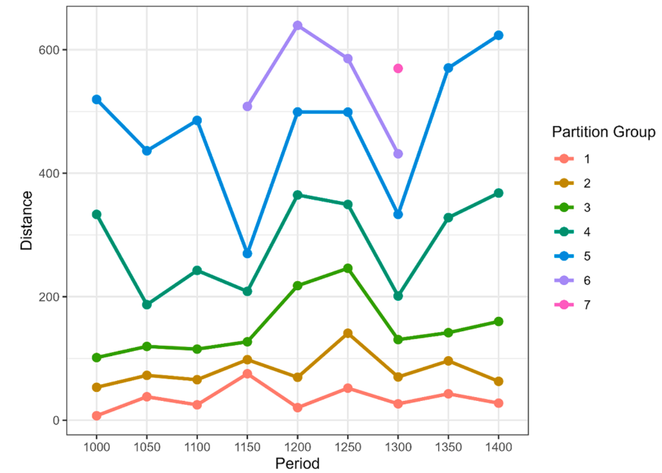

Fig. 6. Plot showing prototypical distances in kilometers through time across all sub-divisions for each interval. Where a given sub-division (6 or 7) is not indicated that sub-division was undefined for the interval indicated.

regional distribution of settlements. Specifically, settlements coalesced into fewer and fewer areas marked by larger settlements with gaps in the distribution over the course of the thirteenth and fourteenth centuries (see Hill et al. 2004; Mills et al. 2013a). Thus, changes in the longest distance critical scales and prototypical distances are perhaps a product of the increased distances between clusters of settlement through time such that comparing spatially expansive network communities between the earlier and later half of the period considered here is somewhat like comparing apples to oranges since the underlying distribution of the upper mode of distances are so dramatically different.

As we have a series of temporally sequenced networks, it is further possible to assess the degree to which prototypical distances and the specific boundaries they entail change or persist through time. Since the specific settlements occupied through time differ between periods, however, we cannot directly compare community assignments. Another useful assessment of change through time could be generated by identifying potential spatial boundaries among network communities and the degree to which they overlap in space for comparisons for different temporal periods. In order to make this comparison, we divide our study area using smoothed Voronoi polygons which represent the boundaries around community assignments across space (Fig. 7). We define these polygons and then select boundaries using the *divchain* function within the *deldir* R package, which retains polygon edges that divide settlements in different partitions for communities that have at least two members (Turner 2021). The areas marked by edges of the Voronoi polygons thus represent areas where the community membership of sites changes substantially across a short distance. The maps in Fig. 7 each show such spatial divisions for a pair of consecutive intervals both for the second prototypical distance defined for each interval (on the order of about 80 kms). We can then assess agreement between intervals by evaluating the degree to which boundaries overlap between intervals. In order to do this, we calculate a buffer of 18 kms around each boundary (which equates to roughly-one day of travel roundtrip from a starting point; see Hill et al. 2015). We then calculated the percent agreement in boundary definition by creating a buffer around each of these boundaries, rasterizing them, and calculating the total percent overlap in raster cells between time periods. The map on the left in Fig. 7 shows about 39 % agreement suggesting moderate relationship between the spatial character of partitions across time periods and the map on the right shows about 23 % agreement suggesting a somewhat weaker temporal relationship though both of these represent pairs of consecutive intervals. Notably the map on the right highlights two intervals on either side of a major regional scale migration which likely dramatically altered the spatial relationships among connected social groups (see also

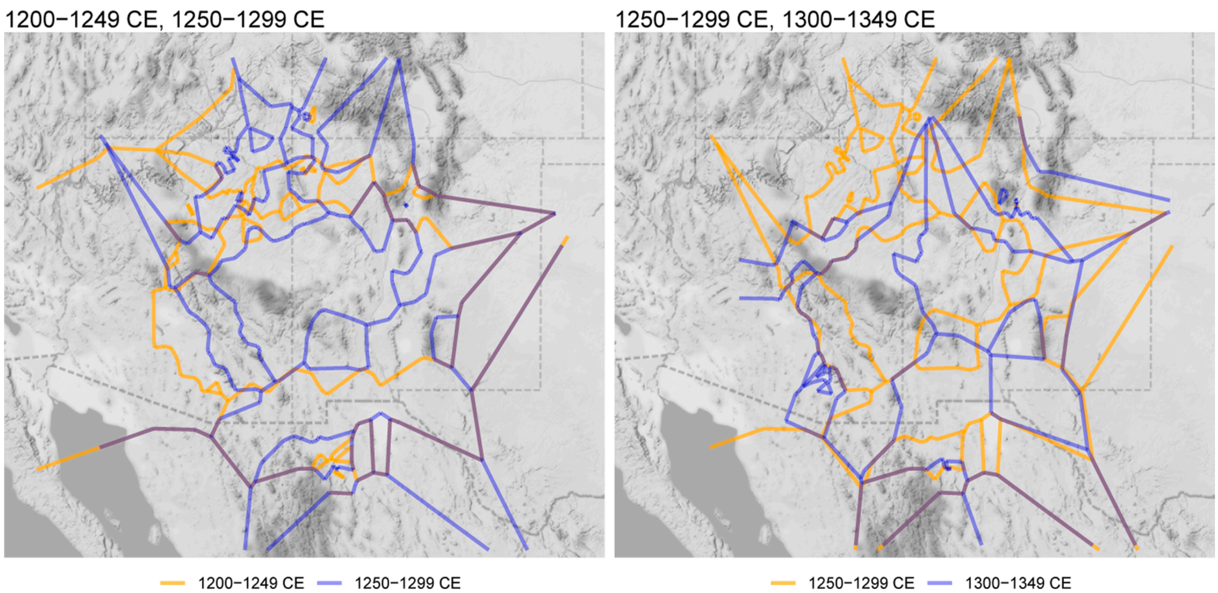

Fig. 7. Maps showing boundaries between network communities for consecutive pairs of intervals. For each map, the orange boundaries represent the first interval and blue represents the second interval. Where the two overlap, boundaries are shown as purple.

Mills et al. 2013a).

When considering overlap across all time periods the spatial boundaries at consecutive intervals are clearly more closely related than boundaries among intervals that are not consecutive. Fig. 8 shows comparisons among consecutive intervals and among non-consecutive intervals. Overall, this suggests that community membership and spatial relationships among communities do have a strong temporal dimension but similarities among intervals separated by more than one time-step (50-years) are considerably lower and drop off quickly. Interestingly, this perhaps gives some indication of the temporal rhythm of spatial network community creation and maintenance in the study area where boundaries persist to a degree across about 100 years but seldom beyond.

6. Discussion

The analyses and results above provide clear evidence of *critical scales* in networks of material similarity in our study area through time. Across all intervals considered from 1000 to 1450 CE we see strong indications of transitions in the relationship between spatial and social distance suggesting that there are a small number of scales across which interaction can be sub-divided. Beyond this, the prototypical distances across which these transitions are typified are remarkably similar through time at short to moderate distances despite major changes in settlement distribution, size, and organization. This finding is similar to the results presented by Menezes and Roth (2017) for their analysis of contemporary geotagged social media data which also illustrated that networks could be decomposed into quite similar distances across a range of locations and geographic scales of analysis (although the absolute scale of the distances involved differ between our study and the contemporary social media data networks).

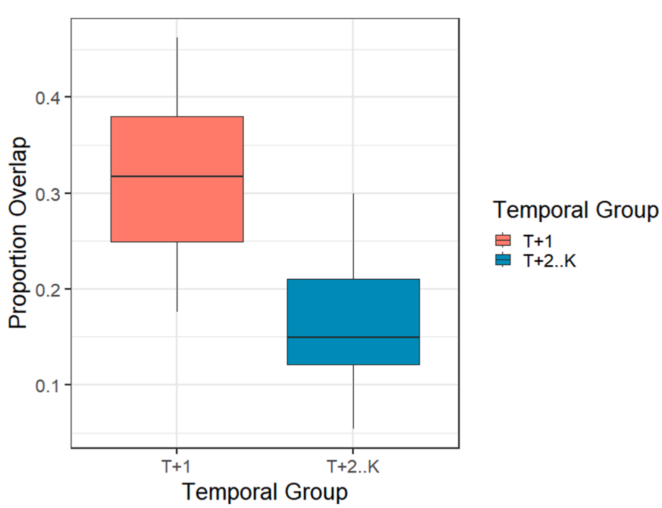

Fig. 8. Boxplots showing the proportional overlap in spatial boundaries between consecutive periods (in red) and non-consecutive periods (blue) for all comparisons.

In our current study, larger partitions at the scale of about 150–200 km or more (which would likely represent many days travel on foot in the ancient Southwest/Northwest) were considerably more variable through time. We argue that these changes are at least in part driven by the changing overall distribution of settlements and distances as portions of the study area saw dramatic reductions in population as population concentrated in fewer locations with larger gaps between them (see Hill et al. 2004). The differences we see between short to moderate distances (<150–200 Kilometers) and longer distances may, in and of itself, provide some indication of the scales across which broad regional networks may have operated. For example, although the archaeological definitions of culture areas are complex and certainly do not encapsulate well-defined social units like contemporary cultures or ethnic populations, such distances are consistent with traditionally drawn boundaries of many such archaeological units. For example, 175 km is approximately the distance from Chaco Canyon to the furthest outlying Great Houses and Great Kivas (architectural features indicative of participation in the Chacoan World). In southern Arizona, a similar distance also captures the outer extent of areas where Hohokam Middle Gila Buffware is common from the production area south Phoenix, Arizona (see Wilcox 1996). This suggests our analysis may be hinting at the scales across which consistent and regular interactions of the kind that generate broad similarities we recognize as archaeological culture areas may operate in the Southwest/Northwest study area.

Another important aspect of the analyses presented above is that this provides a rare opportunity to explore the *critical scales* of network partitions over long periods of time. The results presented above show that network communities and the potential spatial boundaries between them are moderately similar between consecutive 50-year intervals and often quite different if we consider non-consecutive intervals. This illustrates that past network configurations impact subsequent network definitions in detectable ways. Interestingly, this also suggests that network configurations more than about two generations back (more than about 50 years) have relatively little bearing on subsequent network configurations in our study area. In many contemporary studies of network dynamics researchers are interested are interested in topological features that make network resilient (able to retain basic functionality after shocks) to disturbances over comparatively short timescales (Gao et al. 2016). This analysis suggests that when we consider scales across decades or centuries, we may see junctures involving major changes to the overall network topology and transitions that interrupt trajectories of network development. Previous work in the region has hinted at the patterns explicitly identified here. For example, Mills and colleagues (2013a) showed that long-distance migrations from the Four Corners region into central and southern Arizona led to transformations of network structures and scale (including features like network diameter and shortest path lengths) during the period marked by the greatest degree of population movement, but that many network features rebounded to levels similar to those seen prior to the major migration in subsequent intervals. Overall, this suggests an interesting gap in the study of network dynamics which has focused on relatively short timescales that miss these long-term adjustments in network trajectories. We argue that the issue of the temporal scale of network topological trajectories and change is an area that archaeological networks are well suited to contribute to in the future.

As we outlined above, one the primary purposes of identifying *critical scales* and prototypical distances is to define distances across which certain kinds of interaction are concentrated and to postulate what those interactions may be. Given the consistency in prototypical distances through time across our study area, can we evaluate what kinds of interactions such scales may have entailed? To address this, we can first explore the prototypical distances defined here in terms of potential scales of human movement. The mean distance for the smallest prototypical distance across all time periods is 35 km. Although this distance threshold was defined based on partitions created without any spatial information, the value is remarkably similar to the estimated average distance that a burdened traveler can walk in a day which was previously estimated by Drennan (1984) at approximately 36 Kms. Interestingly, the mean value for the next partition is 81 km or a bit more than double the distance represented by the first partition distance. The mean distance for the third partition is 151 km which is again nearly double the second partition distance though notably there is considerably greater variation in this partition distance through time.

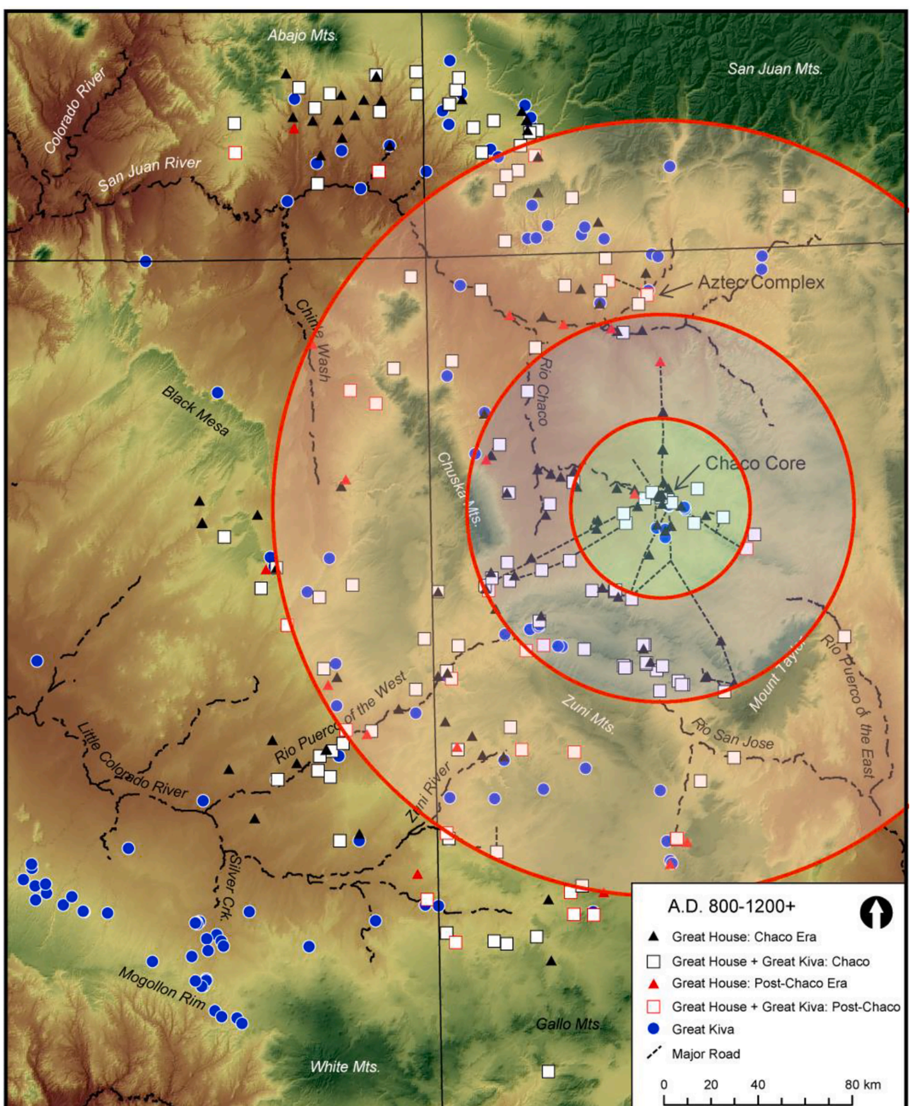

Fig. 9. Map of the Chaco World showing concentric buffers of 35, 81, and 151 km centered on Chaco Canyon.

The consistency in the distance thresholds in network partitions and their relationships to typical estimates for overland travel suggests that the geographic scale of partitions based on ceramic similarity may have been influenced in part by the ease of travel on foot between settlements. The thresholds at approximately 1, 2, and 4 days travel perhaps further suggest natural scales across which different kinds of interaction and activity may have been organized across the region. We might expect food sharing and regular contact to occur across the first distance and for other kinds of resources to flow across the second distance. For example, 80 km is approximately the median distance from the center of its distribution that ceramic wares are circulated in the U.S. Southwest (see Bischoff and Peeples 2020). As noted above, there is considerable variation for the third distance and beyond, but as we discuss above, the range of distances we see for this third critical scale roughly encompasses the scale of archaeological regional traditions. Fig. 9 helps to illustrate the spatial relationships defined by these concentric buffers with regard to the Chaco Canyon area showing our mean critical distances as concentric circles centered on Chaco itself. The first distance threshold includes the canyon and the adjacent Great Houses in the area often defined as the Chaco Halo or Chaco Core (see Lekson 2006) which is seen as the area of most frequent interaction. The next buffer conforms well to the extent of the major roads extending from Chacon Canyon and includes major sources of resources such as wood, lithic materials, and ceramics which were brought into Chaco Canyon. Finally, the third buffer captures most of the areas where great houses and great kivas are most common and notably most of the pre-1050 CE Great Houses.

We are not the first to note such a pattern of nested scales of interaction in the region. David Wilcox and colleagues (Wilcox 1996; Wilcox et al. 2007) described a similar spatial partitioning of settlement systems into regions and macroregions of concentric days of travel around major centers across the U.S. Southwest, and notably drew similar conclusions to those outlined here in terms of the specific buffers and distances involved. For example, Wilcox (1996) suggested key scales across which what he called macroregional polities operated on the order of about 175 km in radius. This was an estimate he generated based on the scale of Chaco Great House and Hohokam ball court communities suggesting an extent at about four to five days travel on foot as the upper limit across which reasonably frequent exchange and interaction could be maintained. Interestingly, Wilcox (1996; Wilcox et al. 2007) past work was based explicitly on the geographic locations and sizes of settlements alone. In the analyses presented here, spatial divisions and prototypical distances are based only on similarities in ceramic inventories between sites defined without reference to spatial relationships. The fact that we see critical scales at similar distances to those identified based on settlement distributions and hierarchies provides further evidence of the close connection between space and social interaction at the scales of frequent human movement.

One additional question that arises from this work is whether there are any predictable features of the landscape (i.e., mountains, canyons, rivers) that might be important delimiters of movement and network community boundaries through time. In order to consider this possibility, we can map all of the Voronoi polygon boundaries defined between network communities for all periods together in a single map with areas where boundaries overlap across multiple time periods indicated by the color scale (Fig. 10). To those familiar with the U.S. Southwest/Mexican Northwest, this map clearly bounds well-defined archaeological regional traditions and regions, which is not surprising given the discussion above. When we look at only the areas marked by boundaries across six or more periods, we can see further interesting patterns. For example, the San Juan River in Northwestern New Mexico appears to have consistently marked the edges of network communities. Further in central New Mexico the area between the Northern and Middle Rio Grande region is consistent through time and importantly this is also an ethnic and linguistic boundary in the historic era. In central Arizona there is a clear and consistent break marked by the Mazatzal Mountains. In this case this physiographic feature, with relatively few major

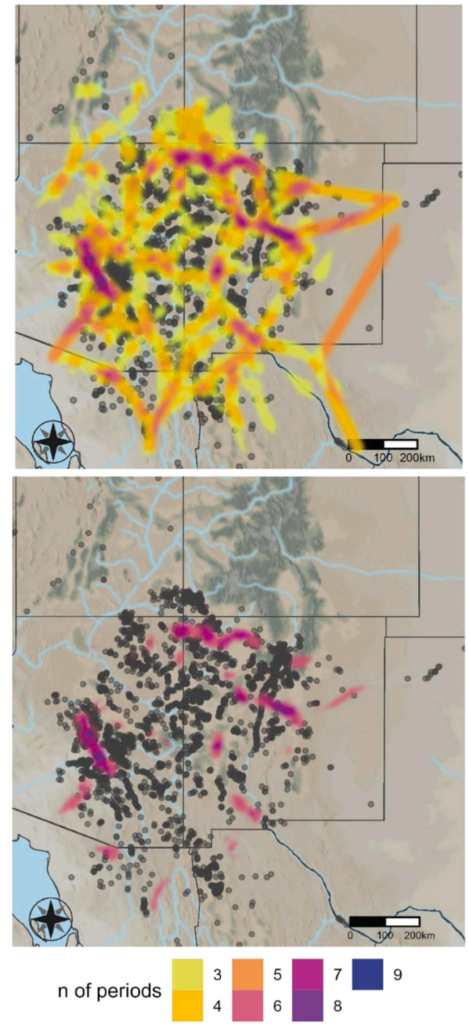

Fig. 10. Map showing overlain boundaries between network partitions for al time periods with the number of overlapping periods indicated. The lower map shows only those areas with greater the 6 overlaps.

settlements found within its boundaries, perhaps presents a barrier to travel which generated a social boundary detectable in the network data. Overall, however, it appears that the most consistent spatial breaks in this study area cannot be easily explained by settlement distribution or physiographic features and perhaps instead relate to persistent social boundaries through time.

7. Conclusion

The analyses here have illustrated: 1) that *critical scales* in networks can be identified using material culture similarity data, 2) that such critical scales occur at similar distance thresholds through time despite major changes in settlement distribution and organization, and 3) that spatial boundaries defined in relation to network communities for one temporal interval influence boundaries in subsequent intervals though influence drops off rapidly through time. Further, this research illustrates that the nested patterns of human movement and mobility in the contemporary world (see Menezes and Roth 2017) have analogs in the ancient past, though the specific distances involved change. This suggests that there were similar constraints on human mobility related to specific kinds of interaction in the past as in the present. Finally, this work also has the potential to expand insights into the scalar nature of networks in this region and generally.

First, as Mills and others (2015) argue, analyzing the historical trajectories of networks at varying scales can lead to complementary insights into the structural properties of those networks. One of the key challenges of such scalar examinations of networks is defining the boundaries across which each scale will be considered. In previous work (Mills et al. 2015) this has been done using traditional archaeological tradition boundaries, but that runs the risk of missing ties that extend across such traditional regional designations. The methods we have presented here illustrates a potential tool for formalizing the creation of hierarchical scales for exploring and comparing network properties and topologies. Such an approach also provides insights relevant for recent research in archaeology and other fields focused on settlement scaling theory (e.g., Lobo et al. 2020; Ortman et al. 2015). Settlement scaling theory posits predictable relationships between settlement size and areal extent and certain aggregate properties of those areas such as the total amount of infrastructure and the rates of socioeconomic outputs per person. The efficiencies of infrastructure and outputs are typically attributed, at least in part, to network effects concentrated at a given scale. Although much of this work has focused on relationships among individual settlements, cities, or metropolitan statistical areas there is further research that suggests scaling relationships may also play out at larger scales among sets of interconnected cities/settlements (e.g., Ortman 2023; Prieto Curiel et al. 2022). The work here focused on identifying critical scales perhaps provides an avenue to facilitate comparisons when exploring scaling relationships above the level of the settlement. Overall, the approach outlined here has the potential to expand our understanding of the nature of network interactions from the micro to the *meso* to the macro scale and also provides a consistent means for defining such units of analysis that would be broadly relevant across archaeological and contemporary network contexts.

CRediT authorship contribution statement

Matthew A. Peeples: Conceptualization, Methodology, Data curation, Writing – original draft, Writing – review & editing, Funding acquisition, Formal analysis, Software. **Robert J. Bischoff:** Methodology, Writing – review & editing, Formal analysis, Software, Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Statement

Data and R code used in this analysis are available on GitHub at https://github.com/mpeeples2008/CriticalScales. Due to concerns for archaeological site security, site locations are not given directly in this repository but instead derived products (distance matrices) are instead presented. All the code that was used to generate these distance matrices is also provided. The raw ceramic data were originally retrieved from cyberSW.org and can also be obtained directly there, though there may be slight differences in cases where site data have been updated since our data were obtained in June 2022.

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