

The Oxford Handbook of Archaeological Network Research

Matthew A. Peeples (ed.) et al.

<https://doi.org/10.1093/oxfordhb/9780198854265.001.0001>

Published: 2023

Online ISBN: 9780191894312

Print ISBN: 9780198854265

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CHAPTER

37 Settlement Scaling Analysis as Social Network Analysis

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<https://doi.org/10.1093/oxfordhb/9780198854265.013.35> Pages 593–607

Published: 20 November 2023

Abstract

Recent work demonstrates the power and potential of network analysis in archaeology. In this chapter, I show that settlement scaling analysis can also be construed as a form of social network analysis. I first illustrate the role of network thinking in settlement scaling theory (SST), a framework that provides a general account of agglomeration effects. I then discuss three advantages of the SST approach relative to popular applications of social network analysis in archaeology: (1) it eases the empirical burdens of empirical network analysis; (2) it leads to specific expectations regarding what the aggregate properties of social networks should be; and (3) it provides a mechanism for the emergence of new properties in human societies. Finally, I suggest a means of integrating scaling analysis with regional archaeological network analysis.

Keywords: [archaeology](#), [networks](#), [settlement scaling](#), [agglomeration effects](#), [urbanism](#), [complex systems](#)

Subject: [History and Theory of Archaeology](#), [Archaeological Methodology and Techniques](#), [Archaeology](#)

Series: [Oxford Handbooks](#)

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Introduction

The most popular applications of social network analysis in archaeology have typically proceeded from empirical social networks that are constructed node by node and link by link. Such networks have been constructed on the basis of site locations and sizes (Fulminante 2012; Johnson 1972), documentary evidence (Sindbæk 2007), trade goods (Irwin-Williams 1977), and measures of similarity in material culture (Mills et al. 2013), what some refer to as archaeological similarity networks. Such studies also typically calculate measures that summarize the network's structure (degree centrality, eigenvalue centrality, betweenness centrality, etc.) to facilitate comparisons across time and space (Brughmans 2013). The purpose of this chapter is to illustrate an additional way network thinking is being incorporated into archaeological analysis. I first illustrate how settlement scaling theory (SST), a framework that provides a general account of agglomeration effects, is grounded in a form of network thinking that abstracts away from the explicit identification of nodes and edges while still seeking to capture aggregate network effects. Then I discuss three benefits of this approach relative to regional-scale empirical network analysis: (1) the empirical burdens of scaling analysis are somewhat less than is the case for empirical network analysis; (2) SST leads to specific expectations regarding what the aggregate properties of social networks should be, making it easier to distinguish general dynamics from historical contingencies; and (3) SST provides a mechanism for the emergence of new properties in human societies that is grounded in network thinking. Finally, I suggest a few areas where both scaling and network analyses could be improved through greater integration of the two approaches.

Settlement Scaling and Networks

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SST is a collection of formal models derived from first principles that predict the average effects of population for the aggregate properties of human networks. Typically, these properties are measured at the level of a settlement, which in this approach is an area that contains a group of people who mix socially on a regular basis. In contemporary societies, the properties considered range from built areas to infrastructural needs (roads, utilities, gas stations) to socioeconomic rates (GDP, crime, disease, patenting). Archaeological proxies for such properties that have been investigated thus far include site areas, house sizes, monument construction rates, plaza areas, inscriptions, road areas, and artifact consumption rates.

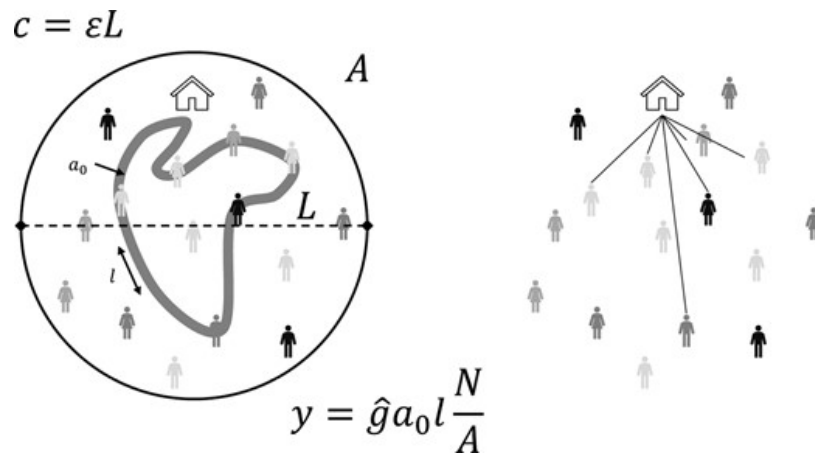
SST was initially developed in the context of cross-sectional analyses of contemporary metropolitan areas (Bettencourt 2013, 2014; Bettencourt et al. 2007; Pumain et al. 2006), but a range of studies have subsequently shown that these relationships apply very broadly, to ancient, non-industrial, non-market, and even non-urban settlements (Cesaretti et al. 2016; Hanson et al. 2019; Lobo et al. 2019; Ortman et al. 2015; Ortman et al. 2014; Ortman and Coffey 2017; Ortman et al. 2016; Smith 2019). The human individual at the center of these models is not the rational, all-knowing, utility-maximizing agent of neoclassical economics (Schill et al. 2019) but is instead a person who seeks to balance the benefits of social interaction with the associated costs, following the tradition in geography (Alonso 1964; von Thünen 1966). The most detailed derivation of these models is given in Bettencourt (2013) and Lobo et al. (2019). Here, I provide a brief abstract, focusing on the role of networks in these models.

The basic relations of settlement scaling emerge from individuals each seeking to achieve a balance between transport costs and interaction benefits through their residential locations and daily movements. The cost for a person to mix socially with others across an area per unit time is given by $c = \varepsilon L = \varepsilon A^{1/2}$ (where ε is the energetic cost of movement and A is the circumscribing area); and the total number of interactions that actually occur (a person's degree) is given by $k = a_0 l N / A$ (where a_0 is distance at which interaction occurs (a cross-section), l is the average path length of an individual per unit time, and N / A is the average

population density of the area). One can translate interactions into benefits by assuming that there is an average net benefit across all types of interaction, $\hat{g}$, such that $y = k\hat{g} = \hat{g}a_0lN/A$. This is a reasonable assumption because if social interactions of all types did not confer a net benefit for individuals there would be no reason for human networks to exist in the first place. Then, by setting $c = y$ and solving for the area in terms of the population, one arrives at $A(N) = aN^{2/3}$, where $a = (G/\varepsilon)^{2/3}$ and $G = \hat{g}a_0l$. Thus, under these circumstances, the area taken up by relatively amorphous settlements grows proportionately to the settlement population raised to the $2/3$ power, such that larger settlements become progressively denser. Note also that the coefficient or prefactor of this relationship $a = (\hat{g}a_0l/\varepsilon)^{2/3}$ varies in accordance with the productivity of interactions, the length of daily movement and transportation costs, but it is independent of population. Figure 37.1 presents a schematic view of this model. Notice that in this model the structure of encounters over a period of time is the social network that creates network effects and connects them with population densities over space.

p. 595 From this simple model rooted in network thinking a variety of predictions emerge. First, as settlements become larger and more organized, interaction increasingly occurs through movement within a second, physical network of roads, paths, and other public spaces. As a result, the relevant area over which interaction occurs is no longer the circumscribing area A , but the area of this physical network, A_n . Previous work suggests that the space devoted to this access network per person r is added in accordance with the current population density, such that $r \propto (A/N)^{1/2}$. As a result, the total area of the access network $A_n = Nr = A^{1/2}N^{1/2}$. Substituting $aN^{2/3}$ for A in this equation, based on the relationship derived previously, then leads to $A_n = a^{1/2}N^{5/6}$. There is still an economy of scale, but the rate of densification is somewhat slower due to the presence of a second, physical network within which the social network must operate.

Figure 37.1.



Schematic depiction of the amorphous settlement model. On the left, N individuals are distributed over a roughly circular area A such that there is a balance between the costs c of moving across the area (given by movement cost ε times the transverse dimension L) and the benefits of the resulting social interactions. A representative agent leaves their residence on a given day and follows a path across the settlement, the area of which is given a_0l . The agent has interactions of different types, denoted by shading of the encountered individuals. The outcomes of these interactions vary, but the average result per interaction $\hat{g}$ is positive. The degree (number of interactions) k experienced by this representative agent over the course of a day will be the fraction of the settlement covered by that person's path, a_0l/A , times N . The network of interactions experienced by this agent is depicted on the right. Since each agent will have her own path and interactions, movement and interaction across agents creates a social network, such that the aggregate outcome of social interaction across the settlement Y will be equal to the outcome for the representative agent y times N . Note that this approach quantifies aggregate network effects without requiring the network to be specified empirically.

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Second, notice that because the outcome of interaction for an individual per unit time is $y = GN/A_n$, the aggregate (extensive) socioeconomic rates Y of a settlement (both positive and negative) can be written as $Y(N) = yN = GN^2/A_n$, and one can thus compute the expected scaling of socioeconomic rates relative to population by substituting $a^{1/2}N^{5/6}$ for A_n . This leads to $y = Y/N = Y_0N^{1/6}$, where $Y_0 = Ga^{-1/2}$ is the baseline rate. This further implies that average per capita rates vary with population according to $y = Y/N = Y_0N^{1/6}$. This means that as settlements increase in population their average per capita socioeconomic outputs grow proportionately to population raised to the $1/6$ power, and total outputs grow proportionately to population raised to the $7/6$ power. In other words, there are increasing returns to scale such that more populous settlements exhibit faster socioeconomic rates.

Finally, note that in larger and denser settlements the average degree of an individual also increases, and this creates opportunities for increasing specialization. Given that each individual requires access to a given number of functions F , an increasing average connectivity k makes it possible for each individual to specialize in a decreasing range of functions d , such that the product $k(N) \times d(N) = F$, with F a constant independent of N . This relation implies that increasing connectivity enables increasing functional specialization (i.e. division of labor), so that if $k(N) = K(N)/N = k_0N^{1/6}$ then $d(N) = (F/k_0)N^{-1/6}$ and the total productive diversity $D(N) = (F/k_0)N^{5/6}$. This means that new specializations emerge as settlements grow and individuals become more highly connected, but these specializations are added more slowly than people.

This brief discussion illustrates that network ideas are central to settlement scaling models, but in contrast to many network analysis approaches, in this case the social and infrastructural networks are treated in aggregate, or on an average per capita basis, as opposed to on a node by node basis. The “network” itself is not real but is an emergent time-averaged structure and accounting device for the cumulative dynamics of social encounters. In addition, these models lead to expectations regarding other aggregate (or average per capita) properties of social groups that emerge from social networks embedded in space and time. The main expectation for the social network of a settlement itself is that the total links between individuals per unit time will increase faster than the number of individuals, but this phenomenon also leads to a variety of other effects related to the use of space, resource needs, information, economic outputs, epidemiological processes, and even violence. This approach does not address all potential properties of human networks, but it does work well in several areas where empirical network analyses have difficulty. I discuss three examples below.

Easing Empirical Challenges

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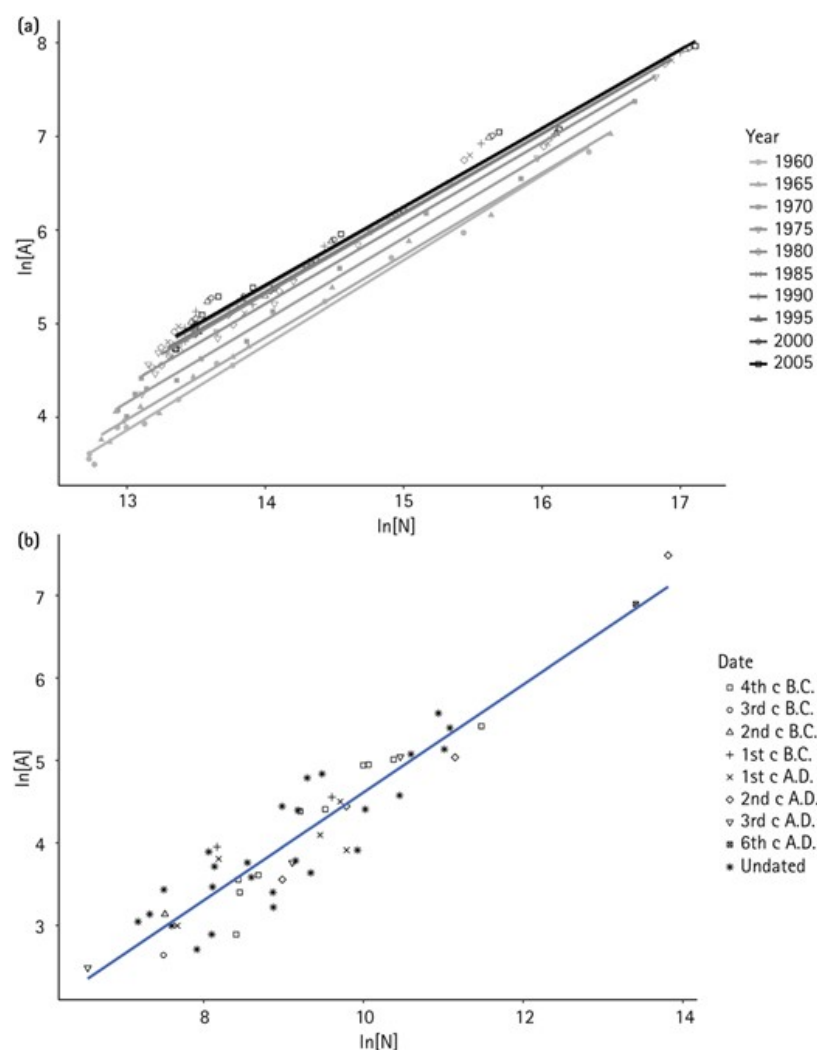
The data requirements for scaling analysis are not trivial. Specifically, one needs to compile measures that are proportional to population for settlements that span the settlement size distribution for a given archaeological period in a region, and additional measures related to the use of space and socioeconomic rates. These can range from simple site areas to dimensions of public works, open spaces, house areas, and artifact assemblage data (Hanson et al. 2019; Ortman et al. 2015; Ortman and Coffey 2019; Ortman and Davis 2019). Importantly, the population proxies must allow for variation in residential density across settlements. So although site area is a useful measure, it cannot be used directly as a population proxy. Most regional-scale archaeological network analyses utilize similar, broadly available archaeological evidence, but in certain ways the data requirements for scaling analysis are more forgiving.

First, most archaeological similarity networks are based on the idea that settlements with more similar material culture assemblages interacted more frequently than settlements with less similar assemblages; but of course settlements that were part of the same, enduring regional network may have different material cultures simply due to the passage of time. So, to construct archaeological similarity networks that

approximate past social networks, one needs to hold time constant as much as possible to approximate a cross-sectional analysis. Network analysts have come up with ingenious ways of approximating this (e.g. Roberts et al. 2012), but such approaches generally require a high density of regional sampling so that change over time in material culture can be tracked reasonably well.

Cross-sectional data are also essential for scaling analysis of contemporary systems because today the heights of scaling relationships, as reflected in the y-intercepts of such relationships, generally change rapidly (Bettencourt et al. 2020). Figure 37.2a provides an example, illustrating the changing relationship between population and built area for Japanese metropolitan areas over a period of 45 years. The chart clearly shows that the height of the scaling relation between these two measures has changed substantially during this period. However, in past societies scaling intercepts appear to have changed much more slowly. Figure 37.2b illustrates this situation using data for a sample of Greek and Roman cities where population was estimated by multiplying the house density in cleared areas by the total site area (Hanson and Ortman 2017). Results like this suggest that it is feasible to recover scaling relationships using data that reflect temporal averages for specific sites, and even sites that were inhabited at different times (Ortman et al. 2015). In a nutshell, analyses of archaeological similarity networks often seek to determine the relative frequency of interaction between settlements based on measures that track these interactions. Scaling analysis, in contrast, presumes that interactions are frequent within settlements, and focuses on measuring the net outcomes of these interactions.

Second, both archaeological network analysis and scaling analysis seek to identify patterns using regional datasets, but the scale of the processes under investigation is different. Whereas most inter-site social network analysis in archaeology seeks to characterize social processes between settlements, scaling analysis seeks to characterize processes that take place within them. So, although both utilize regional-scale data to identify patterns, the intensity of sampling required to adequately characterize regional social networks is much greater than is needed to characterize network effects within settlements in a region. For example, in archaeological similarity networks, two settlements may have been connected in the past via a settlement that lay between them, and this settlement may have a material culture that is intermediate between the nodes at either end; but if data are not available for this intermediate settlement, the fact that the two ends are linked in a single network may not be recoverable. Such issues have led Brughmans (2013) to note that one can create a network using any dataset, but the extent to which such networks reflect past reality is often difficult to determine. Owing to such concerns, practitioners of social network analysis in archaeology tend to focus on the positions of specific nodes in well-documented portions of networks, or aggregate properties of networks overall (Mills 2017). Scaling analysis proceeds directly to these aggregate properties (Below, I suggest that this convergence on aggregate properties opens up exciting areas for integration of the two approaches). 4

Figure 37.2.

Population–Area relationships for contemporary and ancient settlements.

a) Population vs. built area for Major Metropolitan Areas in Japan, 1960–2005. Note that the slope of the fit line is consistent across time steps ($\beta = .858 \pm .023$), as expected, but the intercept of the fit line increases over time ($a_{1960} = .128 \text{ m}^2$, $a_{2005} = 3.274 \text{ m}^2$). Notice also that the size distribution of cities migrated upward over this period. Finally, note that there was relatively little change in the intercept between 1990 and 2005, a period generally recognized as one of stagnation in the Japanese economy. Data from <https://www.stat.go.jp/english/data/index.html>. (B) Population vs. circumscribing area for Greek and Roman cities, 300 BCE to 600 CE Populations are estimated from house densities within cleared portions of each city. Note that the data for each city derives from different centuries but they nevertheless follow a single scaling relationship with slope $\beta = .654 \pm .034$ and intercept $a = 1460 \text{ m}^2$ ($r^2 = .877$, $P < .0001$). This shows that the energetics of social interaction changed very little over time in the Roman world, and as a result the expected scaling relation can be recovered even using limited, imprecise, and time-averaged data. Data from Hanson and Ortman (2017).

p. 599 Third, real social networks are multivariate and involve many different types of interactions, for a variety of purposes, and with a variety of outcomes. A crucial assumption in many archaeological network analyses is that the evidence one has to work with—artifact assemblages, site locations and sizes, sourcing data, and so forth—are reasonable proxies for the overall pattern of interaction between settlements. I do not mean to suggest that this is not often reasonable, only that it is rarely demonstrable. In fact, the relationship between a network representation of data and social reality is an issue even for the present, despite modern accounting (Hidalgo and Hausmann 2009), smart phones (Andris and Bettencourt 2014), the internet, and so forth. The extent to which the data traces of these different forms of interaction capture properties of an overall social network is an open question, even in a contemporary context. At best, these data capture the

network of the specific types of interaction reflected in the data. This does allow one to examine the properties and dynamics of the network; but claims that the network reflected in any particular form of behavior is representative of a larger, multidimensional social network must usually be taken on faith.

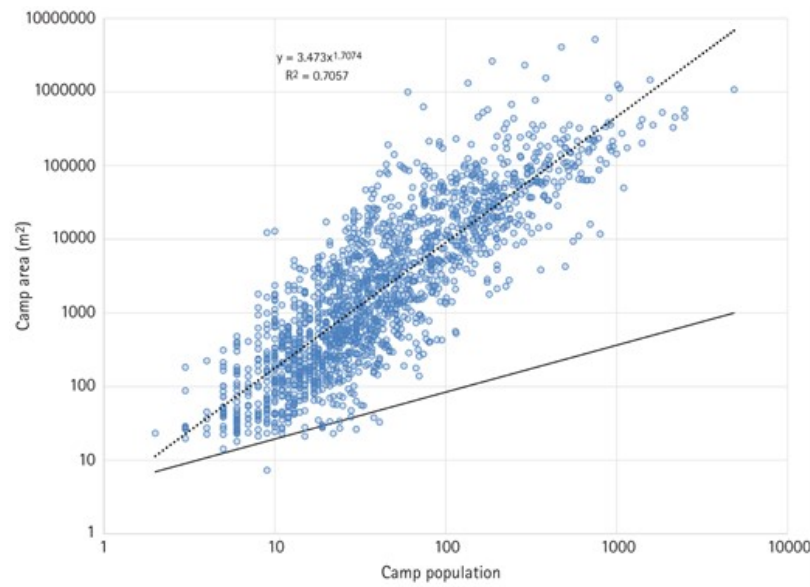
Scaling analysis also works on the basis of material proxies, and it also takes some creativity to transform the available data into aggregate measures of population, resource use, and other socioeconomic rates. But there is a crucial difference, which is that these measures are not seeking to capture specific spatial patterns of social interaction in detail. Instead, scaling analysis assumes that there are all sorts of interactions happening within settlements, and most of these are not directly observable, but their net material effects are observable. In a nutshell, scaling analysis seeks to measure the net material effects of a social network in space, but it does not attempt to observe the network or its properties directly. Here again, the empirical barriers that separate the archaeological record from past social networks seem lower in the case of scaling analysis.

Making Predictions

A second area where scaling analysis does well in comparison to archaeological network analysis involves making predictions regarding the properties of social networks. Applications of social network analysis in archaeology often include calculations of network statistics that summarize global properties of the network: the degree distribution, eigenvalue centrality, betweenness centrality, k-connected components, and so forth. And in many cases these summary statistics can be shown to have changed over time. What has been missing from such studies is a sense of how one might expect the properties of a social network to change, given the situation. Researchers have previously identified changes in network structure that are connected to other changes in a society, but in the absence of a framework that specifies what one might expect to happen, such accounts have limited relevance beyond the specific historical contexts in which they are observed. The settlement scaling approach is different in that it makes specific claims regarding how properties of human networks change with population. In a sense, it provides a null model that controls for the effects of scale. As an example, it specifies what the average degree of individuals in a settlement should be, given its size, and it also provides expectations for how this measure should change over time.

p. 600 This feature of SST creates two important opportunities. First, it creates a situation where one can know when something surprising does occur and it gives one a head start ↵ in determining what the significance of such findings is. A good example is the relationship between population and area in mobile hunting and gathering societies. A variety of studies have shown that among mobile hunter-gatherers, smaller camps are generally *denser* than larger camps (Fletcher 1990; Whitelaw 1991; Wiessner 1974). Figure 37.3 illustrates this pattern using data from a more recent study (Lobo et al. 2022). In the absence of an expectation from SST, one might not recognize the significance of this pattern. But given the expectation that population will increase faster than area when individuals arrange themselves so as to balance movement costs with interaction benefits, this pattern provides evidence that mobile hunter-gatherers do not behave this way. In other words, there seems to be a fundamental difference in the spatial behavior of mobile hunter-gatherers that needs to be accounted for.

Figure 37.3.



Relationship between population and camp area across mobile hunter-gatherer camps in the ethnographic literature. The dashed-line represents the best-fit line to the data, and the solid line represents the expected relation under SST. Note that, in strong contrast to permanent settlements, the slope of the fit line is much greater than one, indicating that larger base camps are less dense on average. Data is from (Lobo et al. 2020).

The fact that these results vary from the expectations of SST helps one to make sense of them. In this case, Lobo and others (2022) argue that this divergent behavior is due to a relationship between social distance and physical distance. Smaller camps tend to be occupied by close social relations who camp close together and interact intensively, but larger camps tend to be occupied by more distant relations who use space to regulate the amount of interaction that occurs. In other words, the average degree of a mobile hunter-gatherer in camp appears to reach a threshold and then remains constant, rather than increasing in an open-ended way with scale. This scenario further suggests a major transition in human sociality associated with the formation of large, permanent settlements and hints at the social and cultural constraints that must be overcome to make such open-ended settlements possible. All of this is brought into focus by having a clear expectation regarding how the properties of social networks should vary.

Another advantage of clear expectations is identifying how specific cases deviate from the expected value. Settlement scaling models use network thinking to predict the *average* effects of population for aggregate properties of settlements, but they do not predict exactly the specific properties of individual settlements, because one would expect these to result from a range of additional factors that are not incorporated into these models. In a sense, scaling analysis controls for the effects of population size, such that researchers can identify and investigate properties of specific settlements that are *not* a product of scale. In the study of contemporary urban systems, deviations of individual cities from a scaling relation (i.e. the residuals) are known as *scale-adjusted metropolitan indicators* (Bettencourt et al. 2010). Figure 37.4 illustrates this type of analysis, using the relationship between population and theatre capacity across cities in the Roman Empire (Hanson and Ortman 2020). In this case, Hanson and Ortman argue the exponent of the fit line ($\beta \cong .33$) in Figure 37.4a reflects the fraction of the city population that needs to witness an event for the information to percolate through the entire city population no more than second-hand (e.g. a path length of two from the eyewitnesses). But it is also important that the audience capacity of theatres in most Roman cities deviates from this average expectation.

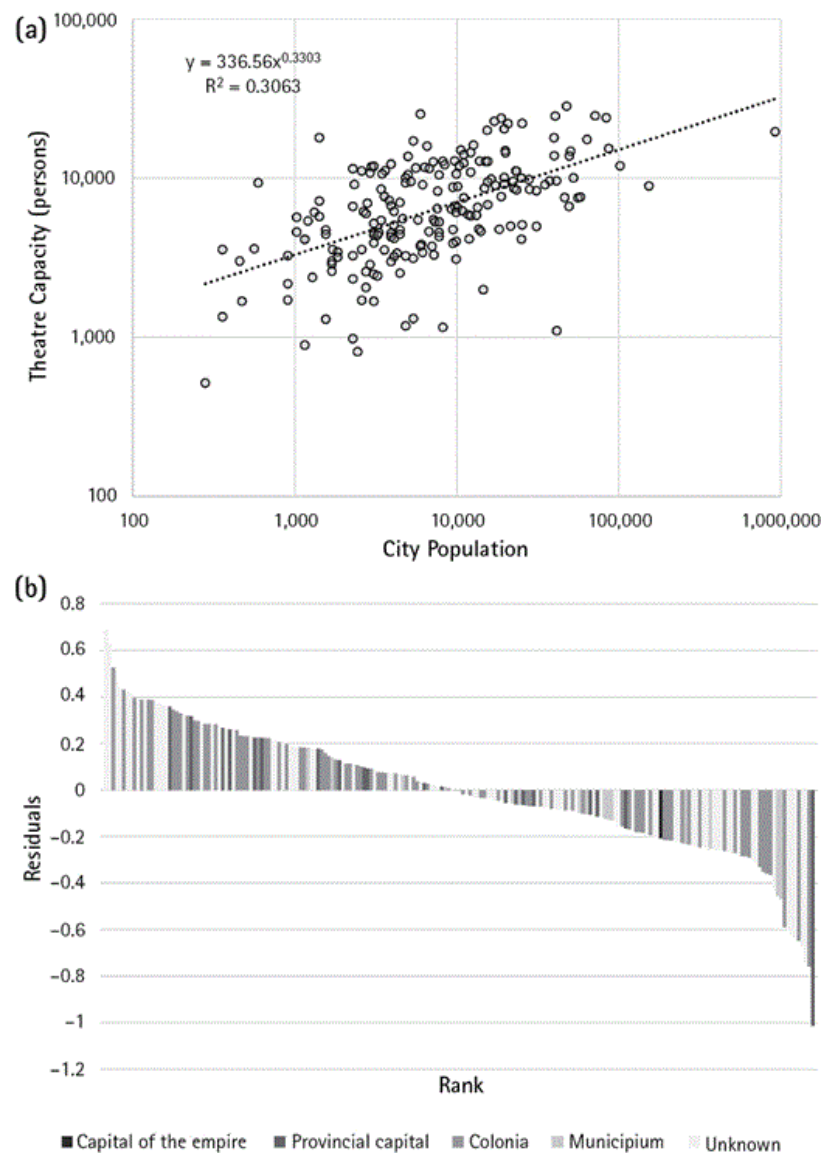
In archaeology, the typical assumption is that such residuals reflect time averaging, measurement error, or a mismatch in time between measures. And certainly, such empirical issues are responsible for at least a

portion of the residuals illustrated in Figure 37.4b. However, there is evidence that in this case the residuals at least partly reflect real deviations in past behavior. Specifically, cities identified by the Romans as provincial capitals tend to have larger theatres than one would expect given their populations (positive residuals), and cities identified as *municipia* tend to have smaller theatres than one would expect (negative residuals). This pattern suggests that the civic status of a Roman city affected the scope of its audience, leading to the construction of theatres that sought to serve these wider social connections. In other words, scaling analysis allows one to learn something about the social networks of individual settlements by examining the degree to which they deviate from the overall scaling relationship. So here again, having an expectation for what should happen helps one to more clearly see cases where it doesn't, and this gives the analyst a head start into a deeper investigation.

Explaining Emergence

A final advantage of the scaling approach is that it provides a means of accounting for the emergence of new properties in human societies. Many cross-cultural studies have found that the population size of the largest settlement is strongly correlated with a range of other properties associated with social complexity, from economic organization to social differentiation, social institutions and technologies (Carneiro 1967; Chick 1997; Naroll 1956). Social network analyses in archaeology have certainly identified the emergence of new properties in social networks themselves (e.g. Mills et al. 2013). SST takes this one step further by suggesting how changes in social connectivity stimulate the emergence of new properties in a society. As discussed earlier, the key relationship is the idea that the range of tasks performed by an individual (productive diversity, which is the inverse of specialization) is inversely proportional to that person's connectivity (degree), leading total diversity to increase in a sublinear way with population according to $D(N) = D_0 N^{5/6}$.

Figure 37.4.



Analysis of theatre capacities across Imperial Roman cities. a) The scaling relation for population vs. theatre capacity. b) The distribution of residuals to the scaling relation, from most positive to most negative, with residuals shaded in accordance with their civic status in written sources. Note the tendency for provincial capitals to have a positive residual and for municipia to have a negative residual. See Hanson and Ortman (2020).

p. 603 Previous studies in evolutionary anthropology have noted the importance of population size and density for technology. In one study, Henrich (2004) argued that the relatively simpler technology of ethnographically documented Tasmanians reflects a loss of knowledge due to imperfect cultural transmission following their isolation from the Australian mainland during the Holocene. In another, Powell and others (2009) argued that the cumulative culture of modern human societies could only get going once a critical population density was reached. Finally, Kline and Boyd (2010) examined ethnographic data on the populations and technologies of Polynesian island societies in arguing that larger populations maintained more diverse repertoires of fishing tools. These three properties—population size, density, and heterogeneity—are also the three components of Louis Wirth’s (1938) classic definition of the city. Of course, the large populations, high densities, and extreme division of labor that characterize today’s cities did not characterize smaller-scale communities of the past. But SST suggests that the social networking processes behind these properties operate the same way in smaller-scale settlements of the past as they do in metropolitan areas

today. As a result, SST provides a framework for studying the emergence of new properties in human societies.

The key mechanism behind such emergence is the increasing connectivity of individuals, which allows for increasing specialization and the accumulation of distinct activities and their associated physical capital. A key measure of social complexity is simply the number of distinct specializations, technologies, institutions, and structures that are maintained by human aggregates. In the ethnographic record this number correlates with community size, and its elements accumulate in a specific sequence, forming what is known as a Guttman scale (Gell-Mann 2011; Peregrine et al. 2004). Such scales have also been identified in archaeological contexts. For example, Chase (2016) uses LiDAR survey to examine urban services provisioning at Caracol, an extensive Classic Maya settlement. His analysis found that plaza groups at the termini of the road network tend to have fewer residences, small temple structures, and a plaza; but groups closer to the center also have ballcourts, reservoirs, and administrative structures, appearing in that order, along with a greater number and density of residences. The overall pattern suggests that larger aggregates support a wider range of services, as indicated by their material manifestations. As the number of people in an aggregate grows, new properties of that aggregate emerge and materialize in a cumulative fashion.

The emergence of these new properties requires increasing specialization (and increasing agricultural output per farmer), and it also requires increasing interdependency between the individuals in the aggregate. All these processes are embedded in SST, in that the balancing of movement costs and interaction benefits leads to increasing density, and increasing density leads to increasing aggregate connectivity, productivity, and diversity. In short, the SST framework specifies how social networking leads to the emergence of new properties in larger aggregates that cannot exist in smaller aggregates.

Expanding the Range of Network Thinking

p. 604 The construction of archaeological networks and their analysis using the tools of social network analysis are both important advances that are generating exciting insights on a range of social processes, from migration (Mills et al. 2018) to community formation (Crabtree, Bocinsky et al. 2017) to resilience (Borck et al. 2015; Crabtree, Vaughn, et al. 2017). The purpose of this chapter has not been to question these developments. Instead, I have sought to call attention to an additional way that network ideas are being incorporated into archaeological practice. I have shown that network thinking occupies the center of settlement scaling theory and its associated methods of scaling analysis, and I have illustrated several areas where scaling analysis seems to have advantages relative to certain forms of archaeological network analysis; namely, more modest data requirements, concrete expectations that allow one to identify noteworthy results, and a mechanism through which one can investigate the emergence of new properties of a society as the properties of its associated human networks change.

However, it is important to recognize that thus far scaling analysis has only rarely addressed human networks above the level of settlements, and this is precisely the level at which most archaeological network analyses operate. For example, in a recent study Peeples and Mills (2018) show that across the late prehispanic US Southwest there are general relationships between local population density (measured as sites within a floating 9km buffer), ceramic ware diversity (measured by Shannon Information), and the fraction of weak ties between settlements (indicated by ceramic assemblage similarity scores in the range $0 < S_{ab} < 0.5$). These relationships suggest decreasing local density is correlated with increases in both ceramic diversity and weak ties. Importantly, these patterns are apparent across the entire region, and over at least a 200-year period. The quantities in this analysis—people, space, interaction, and diversity—overlap substantially with those emphasized in scaling analysis. The primary difference lies in the spatial units. In the Peeples and Mills study, a floating buffer was used to define constant-sized areas within which

properties of the focal site and the associated buffer were measured; whereas in scaling analysis spatial units capture mixing populations of variable size, and aggregate properties are measured for these generally smaller spatial units. In settlements the temporal rhythm of social mixing is daily, but there is no theoretical reason why scaling analysis must be limited to daily interaction. If one could define spatial units at which social mixing was periodic, seasonal, annual, or even generational, one would expect scaling relations to be apparent in the aggregate properties of these units as well. To the extent that interaction at some temporal frequency is the basis for these units, one would expect the techniques of social network analysis to be very useful for defining such units. In this way, it may become possible to integrate social network analysis with scaling analysis, and thereby extend SST to larger-scale spatial units.

My hope is that researchers who work with archaeological networks will be encouraged by this chapter to seek out new ways of connecting social network analysis with scaling analysis. Network thinking lies at the core of both approaches, and it therefore stands to reason that the two can be profitably connected with additional effort.

Acknowledgments

Portions of this research have been supported by a grant from the James S. McDonnell Foundation (#220020438). I thank Jessica Munson, Tom Brughmans, Luis Bettencourt, Jose Lobo, and Michael Smith for many helpful comments on previous drafts.

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