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Complexity Theory

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Perhaps the one theoretical position available to archaeologists today that has the potential to integrate culture history, processualism, and post-processualism is the study of complexity and complex systems. Not to be confused with political complexity and the rise of social hierarchies, complexity theory is the study of how new complex properties emerge from the interactions of many agents interacting in often quite simple ways. But the properties that emerge from those simple interactions are nonlinear, complex, and not predictable from the study of the individual agents themselves. This chapter follows the recent publication of our book *Complex Systems and Archaeology* (Bentley and Maschner 2003a), and necessarily recapitulates much of its first three chapters. However, in the few years since that book was published, there was much for us to update, as complexity theory has grown at an accelerated rate (figure 15.1).

<Figure 15.1>

Background: The Need for Complexity Theory

As a theme of archaeological theory, sorting out the causes and effects of interacting agents might be the most challenging. In fact, a major theme of post-processualism in the 1980s was that there are too many possible explanations for the archaeological record to consider any one right, or scientific, and the others wrong (Wylie 1982; Patrik 1985; Shanks and Tilley 1987; Tilley 1989). Others, however, while recognizing the futility of strict, hypothetico-deductive laws such as, “If object A is found in context C, then behavior B took place” (Fritz and Plog 1970; Schiffer 1972; Watson et al. 1974), still saw more promise for archaeology as a scientific method for interpreting the history of events (Hawkes 1968; Wylie 1982; Flannery 1986; Dunnell 1992; Morgan 1973, 1974; Hodder 1982:11–27; Salmon 1982; Binford 1986; Sabloff et al. 1987; Mithen 1989; Bell 1994).

In fact, the early proponents of systems theory in archaeology (see Watson, chapter 3) rightly pointed out that there are no simple one-to-one mathematical relations to explain prehistoric events; in other words, their causes were multivariate (Clarke 1972: 29–44; Flannery 1967, 1968, 1986). Because computers were not powerful enough at that time to explore (one by one) all the different possibilities for a given multivariate problem, systems theory was necessarily grounded in the much simpler belief that equilibrium is the natural, resting state of social and economic systems. It was supposed that a human system was not *in* equilibrium, then it was *trending toward* it, such that it went from one steady state to another. The origin of agriculture was explained by Flannery (1967) as the result of a cultural system in one state (hunting and gathering) that drifted gradually through *positive feedback* into a succession of new steady states, each one slightly more agricultural than the next. Positive feedback is the phenomenon whereby a change in one direction makes the system even more prone to keep changing in that direction, whereas with *negative feedback* change tends to be counterbalanced, continually guiding the system back toward its current equilibrium, or steady state. Social dynamics often show negative feedback when someone does something abnormal, and other people contest the novel behavior in some way (Henrich and Boyd 2001).

One might see the oxymoron here: how can change occur through equilibrium states, when equilibrium is by definition a *stable* state maintained by negative feedback? Equilibrium implies that the system is closed; if an artist hosts a private party, people with their drinks may drift over now and then to look her new painting, while the guests generally remain in the “equilibrium” state of being relatively evenly distributed around the room. On the other hand, nonequilibrium requires openness; put a famous painting in an open museum and there will be a small crowd around the painting all day, with people continually entering and leaving the cluster, even while the rest of the room remains empty. Because public systems are usually open, nonequilibrium is the basis for models of pedestrian behavior (Batty 2003), and even the formation of trail systems (Batty 1997; Helbing et al. 1997).

Similarly, on a larger scale, societies are always in flux: people come and go, new crops are raised and harvested, and new artifacts are continually created and then discarded. Archaeologists and social scientists often use the word “habitus” to refer to the culturally constrained way of doing things (Bordieu 1977; Dietler and Herbich 1998). Perhaps if people lived forever, they might get so set in their ways that the habitus would crystallize as a closed system, never to change. Thanks to the cycle of life, however, each new generation learns the culture and brings a limited amount of change to it.

Emergence

Complex open systems, not at equilibrium, are said to exhibit *emergent properties*, which are overall patterns greater than the sum of the parts, such that the system may act coherently without domination by a central source (Holland 1998). This is a special interest to physicists, who study the transitions of behavior from one scale to another scale:

> The ability to reduce everything to simple fundamental laws does not imply the ability to start from those laws and reconstruct the universe . . . Instead, at each level of complexity entirely new properties appear, and the understanding of new behaviors requires research which I think is as fundamental in its nature as any other. (Anderson 1972:393)

Thus the quantum mechanics that applies to the behavior of atoms is not useful at the macroscopic scale of solid matter. As we move outward in scale, quantitative aspects become qualitative, and new quantitative aspects emerge from the collective whole. Although the use of the term *emergent property* is relatively new, the same idea in other guises has been discussed in archaeological theory for decades (Clarke 1973; Renfrew 1978; Dunnell 1980; Johnson 1982; Binford 1981, 1986). Robert Carneiro (2000) argued, for instance, that the quantitative increase in population beyond a certain threshold brings about a qualitative change in the structure of a society. Leo Klejn argued in 1973 that once we abandoned our preconceived notions about systems theory, we might be able to investigate the emergent properties that seem to arise out of behavioral interactions (Klejn 1973). Even earlier, ideas like Adam Smith’s invisible hand suggest an emergent property of society (McGlade and van der Leeuw 1997:9; Read 2002). The anthropologist Herbert Spencer (1860) found that societies were emergent (like organic organisms) in three respects:

> (1) That commencing as small aggregations they insensibly augment in mass; some of them reaching eventually perhaps a hundred thousand times what they originally were; (2) That while at first so simple in structure as to be almost considered structureless, they assume, in the course of their growth, a continually increasing complexity of structure; (3) That through their early undeveloped state there exists in them scarcely any mutual dependence of parts, these parts gradually acquire a mutual dependence, which becomes at last so great, that the activity and life of each part is made possible only by the activity and life of the rest. (Spencer 2004:27)

This resembles Anderson's (1972) physics, in that Spencer (1860) saw human society as something that grew from small, independent groups to complex aggregations of components that were interdependent on several scales. Similarly ahead of his time, Durkheim (2004:89) proposed that a "social fact" (i.e., cultural norm) is greater than the collective sum of the individuals, and is "found in each part because it exists in the whole, rather than the whole because it exists in the parts." In other words, it is an emergent property.

What Spencer, Durkheim, Anderson, and others were getting at has now become the subject of complexity theory—the study of emergent properties of systems of interacting components. In any society, where people are simultaneously adapting to each other and the future is unpredictable, how does coherent organization of interdependence emerge? Emergent organization can be as superficial as sports fans doing the "Mexican wave" (Farkas et al. 2002) in a stadium or the self-synchronizing applause at a classical concert (Néda et al. 2000), or it can be as profound as the remarkable, undirected ability for a group of individuals to generate a collective intelligence greater than any one of its members (Surowiecki 2004).

We must be careful not to let the language of complexity theory become our latest source for important-sounding metaphors for things we do not understand (McGlade 2003). The term "emergent property" is a prime candidate for misuse, but when explored properly it can provide compelling insight. For example, by demonstrating that collective wisdom can only emerge when a group possess four specific qualities—diversity, independence, decentralization, and aggregation—Surowiecki (2004) provides useful means for improving group behavior or possibly, for the archaeologist, identifying reasons why certain societies succeeded better than others in the past.

A Ubiquitous Emergent Property: The Power-Law Distribution

One particular emergent property is quantitative, widely discussed, and widespread among complex systems. Having had a special, almost mystical appeal to researchers in physics, biology, ecology, economics, and human society, this property is a mathematical distribution of quantities that follows a power law—a function of some quantity, P, that is proportional to some exponent of another quantity, r:

$$P(r) = C/r^a \,, \qquad \text{eq. (1)}$$

where C is a constant and a is the exponent. When plotted as a function of r, the function P is a highly skewed, constantly decreasing distribution, in contrast to the symmetric bell shape of the normal curve, for example (figure 15.2). A special quality of a power law is that it looks the same no matter what scale it is plotted on. If both axes on the plot are made logarithmic (e.g., powers of 10 such as 1, 10, 100, 1000, and so on), a power law appears as a straight line. For this reason, power-law distributions are often referred to as "scale-free" because as one zooms in or out in perspective, the relationship between the scales is the same. Thus a power-law distribution of individual wealth could mean that millionaires are seventy times more numerous than billionaires, billionaires are seventy times more numerous than trillionaires, "thousandaires" seventy times more numerous than millionaires, and so on. The power-law distribution differs from the distributions most often expected for natural phenomena, such as the normal distribution, which implies an average or "normal" behavior, or the Poisson distribution, which has an outer limit and applies if previous outcomes have no effect on the future, as with flipping

a coin repeatedly. Unlike these distributions, a genuine power-law distribution does not have a characteristic average value, nor is it limited, meaning that any size phenomenon is possible.

<Figure 15.2 a, b>

The reason they have attracted so much attention is that power laws (or closely related functions) characterize a wide range of phenomena. Many see this as profound (Kauffman 1995; Bak 1996; Barabási 2002), while others caution that it could be mathematical coincidence (West and Deering 1995; Newman 2000). In any case, power laws are ubiquitous (Buchanan 2001), occurring among such diverse phenomena as economic market fluctuations (Lux and Marchesi 1999; Ormerod 2005), the growth of modern companies (Axtell 2001), the World Wide Web (Huberman et al. 1998; Huberman and Adamic 1999; Albert et al. 1999), Hollywood actor networks (Barabási and Albert 1999), university research funding (Plerou et al. 1999), the Billboard music charts (Bentley and Maschner 1999), the size of wars in history (Roberts and Turcotte 1998), and even words in the English language (Ferrer I Cancho 2001; Solé et al. 2005; Zipf 1949:26).

There are many ways in which a power-law or similar "fat-tailed" distribution can come about (West and Deering 1995; Laherrère and Sornette 1998; Newman 2000); they generally have one thing in common—they are multiplicative processes, that is, the result of one rule being repeatedly enacted, as in the example above of the iterated equation. One of the most common multiplicative processes among human societies is the rich-get-richer phenomenon. In addition to material wealth, much of what we possess is bestowed on us by others such that the more we have, the more we continue to acquire. A rich person gains more wealth by using that wealth, popular people meet more friends through the friends they already have, people who have attracted sexual partners in the past are the most likely to attract others in the future. High-status leaders are the most likely people to attract additional followers and thus achieve higher status (Henrich and Gil-White 2001). In the social sciences, new power-law distributions are being discovered all the time, such as for the number of sexual partners that people have had in their lifetime (Figure 15.3), the connectedness of Hollywood actors (Barabási and Albert 1999), or even the popularity of baby names (Hahn and Bentley 2003) and dog breeds (Herzog et al. 2004). The sizes of modern cities is also power law distributed (Zipf 1949; Pumain 1997), partly because the bigger a city is, the more people it attracts. Surprisingly, few archaeologists refer to the latter when discussing the primate distribution in the rank-size analysis of archaeological sites (Drennan and Peterson 2004), but this is changing as Brown and Witschey (2003) demonstrate that Maya settlement patterns and hierarchies can be modeled with fractal geometry and that there are power laws of settlement size that at various scales of analysis.

<Figure 15.3>

A widespread and well-studied power-law distribution in the social sciences is that of material wealth, which is ubiquitous for a wide range of economic scales in Western capitalist societies (Pareto 1907; Mandelbrot 1960; Atkinson and Harrison 1978; Bodley 1999). Even in ancient Egypt, wealth appears to have been power-law distributed (Abdul-Magd 2002). If we roughly assume in a Marxist sense (see McGuire, chapter 6) that one person's wealth or power is accumulated through the efforts of others, then that wealth or power ought to be roughly proportional to the number of people within that person's (direct or indirect) influence. If so, a power-law distribution of wealth would imply that the distribution of beneficial connections is also a power law.

Bouchard and Mézard (2000; Ball 2004:281–310) created an abstract model that allowed for the exchange between agents and produced a power-law distribution of wealth. The model included a measure of the proportion of each agent's wealth that it spends on other agent's goods or services (Bouchard and Mézard 2000:eq. 7). Interestingly, Bouchard and Mézard (2000) found that the power law of the wealth distribution became steeper—less inequality—as the degree of exchange was increased. The same result was found by a model of agents within a small, clustered social network, whose members competitively exchange two types of products with each other (Bentley et al. 2005). Compared to no exchange at all, allowing a small amount of exchange produced a high degree of wealth inequality, with a power-law distribution, but increasing exchange beyond that caused the wealth inequality to decrease (Bentley et al. 2005). In other words, while exchange is required to produce wealth inequality, wealth becomes more evenly distributed as exchange becomes widespread.

The same rich-get-richer phenomenon occurs in non-Western societies, such as among pastoralists, whose principal form of wealth is livestock (Mace 1998; Salzman 1999; Hayden 2001). Several ethnographic studies show ownership differing by as much as two orders of magnitude among some groups (figure 15.4). The exponential (Poisson) distributions (figures 15.4a–b) indicate that for those groups, the owners of many livestock are no more likely to acquire more in the future than anyone else. On the other hand, the distributions with power-law "tails" (figures 15.4d–e) suggest that those with many livestock are the most likely to acquire more in the future. These characterizations are supported by the observed natures of these different groups. The political organization of the Karomojong (figure 15.4a) is characterized by basic equality between members of each age set (Dyson-Hudson 1966; Salzman 1999:34). For the Ariaal, family wealth and community authority are positively correlated (Fratkin 1999), and consequently the wealth distribution has a longer tail (figure 15.4c). The Somali (figure 15.4d), among which "life is intensely competitive" (Lewis 1963:110), have the wealth distribution that is closest to a power law (figure 15.4d).

<Figure 15.4 >

In this way, more egalitarian groups have exponential distributions while competitive groups tend toward the power law. On the cooperative end, pro-social traits often promote the well-being of others (Bowles and Gintis 2000:1418; Henrich and Boyd 2001). Any degree of charity or sharing between families to support poor families will flatten out the low end of the distribution. On the competitive end, wealth inheritance and agglomeration of power contribute to the rich getting richer. Among some pastoralists, owners of large herds form alliances such that they expand at the expense of smaller groups (Sahlins 1961; Salzman 1999:40).

In principle, power laws may emerge not just with material wealth but with prestige as well, through the same rich-get-richer process. Henrich and Gil-White (2001) describe the prestige of a model (i.e., object for others to emulate) as being equivalent to "the size and lavishness of a given model's clientele." Because this size and lavishness is the main cue that others use in deciding whom to copy (Henrich and Gil-White 2001:174–178), those who have prestige tend to become more prestigious (Bentley and Shennan 2003). Among hunter-gatherer groups that share food, prestige is gained by sharing the meat from a kill (Altman and Peterson 1987). This is how prestige is accumulated by a single hunter, because the prestige he gained

with his last kill means he will be assisted on future hunts, and that much more likely to continue his success (Barnard and Woodburn 1987:21). So while sharing prevents wealth inequality among hunter-gatherers, it can actually promote the inequality of *prestige*.

Discovering whether this prestige follows a power-law distribution is theoretically possible; it just requires some (albeit indirect) means of quantifying it. In archaeology, there are ways of attempting this (see Ames, chapter 28*)*. For example, through use of a similar technique to that developed to investigate corporate household size and inequalities on the north Pacific (Maschner and Bentley 2003), the lengths of earthen long barrows in southern England (Ashbee 1970), correlated with the labor expended on burying the person, may be a proxy for prestige; figure 15.5 shows that the distribution of barrow lengths is clearly that of a power-law tail. Hence this distribution elegantly includes, as part of a single process, even the largest barrow, which other analyses (Hodder 1979:142) would see as an outlier, needing an exceptional explanation.

<Figure 15.5>

Closely related to prestige, power laws also characterize the growth and power of human corporations. Numerous mathematical models of other growth processes show good agreement with the empirical growth dynamics of corporations (Gibrat 1933; Stanley et al. 1996; Amaral et al. 1998). It has been shown that the sizes of firms in the United States are power-law distributed (Axtell 2001). Other emergent properties have been observed; Stanley et al. (1996) found that, for companies of similar size scales, growth rates actually follow a tent-shaped distribution, which is a bit like the normal distribution, except that the tent distribution decays faster (exponentially) away from the mean on both sides. Stanley et al. (1996) found that the width of this tent distribution was related to the size of the firm as a power law. Remarkably, this applied to all firms, whether they made cars, paper, or pills. An important implication is that the largest organizations have the smallest deviations in growth rates. In other words, in addition to being the most rich and powerful, the largest organizations are also the most stable. In this way, the model could be tested regarding the growth of prehistoric organizations such as chiefdoms, particularly with regard to the stability of their hierarchical organization (see Barker, chapter 29).

The potential applicability of these studies to prehistoric corporate organization (sensu Blanton et al. 1996) can be seen in a model of corporate growth by Amaral et al. (1998), which only required three principal suppositions: (1) firms are hierarchical and composed of relatively independent subunits, (2) the minimum required sizes of firms are broadly distributed but also dependent on the industry (Automobile companies must be larger than software consultants), and (3) the growth rates of divisions within the same firm are independent of one another. Amaral et al. (1998) proposed that the subdivisions within a firm grow in a random multiplicative manner, such that the future change in the size of a company division is proportional to its current size. An important additional feature was that a division could be absorbed by, or break away independently from, its parent firm, depending on how small or large (respectively) it became. In this way large divisions could grow by absorbing smaller ones. The model of Amaral et al. (1998) fit the data that Stanley et al. (1996) had discovered on real companies in the modern economy. What the Amaral et al. (1998) model showed was that simple multiplicative growth was not enough, and that a model of corporate growth needed to account for (1) the subdivided nature of firms and (2) the broad range of minimum size requirements for firms (De Fabritiis et al. 2003). These general models are waiting to be analogously explored by archaeological theorists on prehistoric organizations, with the "firms" becoming prehistoric groups of sizes from bands to chiefdoms to states, and the "splitting off of subdivisions" representing instead the fissioning of groups (Carneiro 1970).

In sum, power-law distributions often characterize the competitive acquisition of properties, such as wealth or number of people under a leader's influence, which arise in human society. A power-law distribution can simply be the result of a growth process in which the most likely agents to acquire more of something are those that already possess a lot of it. For archaeologists, recognition of this potentially quantifiable rich-get-richer process could provide insight into the transition to new forms of society, especially through contact with other groups.

Networks

Archaeologists often discuss *networks*—social networks, trade networks, political networks—and network structure is often seen as a primary determiner of change in prehistoric society (Johnson 1982; Renfrew 1974; Blanton et al. 1996). Networks have other archaeological applications as well. In chapter 17 of this volume Liane Gabora discusses the evolution of the modern mind in terms of a neutral network. Hence it is quite useful that complexity theory has involved an explosion of interest in networks, which cover anything that can be represented abstractly by dots and lines. Network theorists have attempted to model an astonishingly wide range of phenomena, from atomic reactions, gene interaction, bioichemical reactions, ecosystems, human relationships and even language—all have been recently studied as network phenomena (see Barabási 2002 for a review). Two of the most studied models in network theory, and common to most these specific applications, have been (1) small-world networks (Watts and Strogatz 1998; Watts 2003) and (2) scale-free networks (Barabási and Albert 1999; Barabási 2002).

Small-World Networks

The small-world phenomenon is one that many of us know intuitively and is studied keenly by social scientists (Kochen 1989; Granoveter 2003). It refers to the fact that people can experience familiar, close-knit communities and yet still be only a few steps (connections) apart from almost anyone else within a much larger network. In a classic sociological experiment, Milgram (1967) asked different people living in the American Midwest to try to convey a letter to a stranger in Boston, about whom Milgram provided some information, simply by mailing the letter to an acquaintance who might help forward the letter to its target. That friend or acquaintance would be asked to do the same, and so on until the letter reached its destination. Milgram (1967) found that the median number of intermediaries in the letter chains was about five or six, indicating that most everyone in the United States is surrounded by "six degrees of separation."

In a now famous article in *Nature,* Duncan Watts and Steven Strogatz (1998) used a simple model from graph theory to explain the small-world phenomenon. In order to make their analysis, Watts and Strogatz (1998) quantified two essential variables to describe a given network: (1) clustering, which is the degree to which the connections of a typical node are also connected to one another, and (2) characteristic path length, which is the typical number of network links between one agent and another. Then, on a highly simplified ring network of nodes and connections, Watts and Strogatz (1998) explored the changes that occur as the connectivity of the networks is transformed (figure 15.6). At one extreme is the regular network (figure 15.6, left), in which each agent is connected to its four immediate neighbors. A regular network is highly clustered because all connections are local, and it also has a large characteristic

path length because crossing the network requires many small jumps between neighboring agents. At the other extreme was their random network (figure 15.6, right), in which each node was randomly connected to four others anywhere within the network. Since connections are made without preference for those closest to the agent, the random network is not clustered, and because there are so many shortcutting links across it, its characteristic path length is short.

<Figure 15.6>

The breakthrough for Watts and Strogatz (1998) was their discovery of a realm between these two extremes, the small-world network (figure 15.6, middle), which is almost as clustered as a regular network, but its characteristic path length is almost as short as for a random network (Watts and Strogatz 1998). In the small world, an agent perceives itself to be in a clustered neighborhood, and yet the communication distance to any other agents is much shorter than if all agents were equally well connected (Watts and Strogatz 1998).

The advantage of this definition is that the small world is quantifiable, as it has a high clustering coefficient and a short characteristic path length. Watts (1999:142–145) showed that Hollywood is in fact a small-world network, in which a connection between actors is defined as having acted in the same movie. Another small-world network is that of scientists who collaborate with each other (Newman 2001; Guimerà et al. 2005), with authors being the nodes and coauthorship being the connections.

Although prehistoric network connections are naturally harder to quantify, the small-world model is no less relevant for archaeology. For instance, the nodes of a prehistoric network might be Neolithic households, linked by kinship bonds, as part of a small-world network in Neolithic Europe (Bogucki 2003). It may only have taken the traffic of a few individuals journeying between distant trade centers to change a "down-the-line" trading system (Renfrew 1975) into a prehistoric small-world network across a large area. From an ego-centered point of view, the small world means that one has about the same number of contacts at each spatial scale, that is, a Neolithic woman might have a dozen people in her family, know a dozen people in her village outsider her family, have met a dozen people from other villages in the area, and have run across (in her lifetime) a dozen or so tradesmen who passed through from distant regions. Because the woman knows a handful of people on each spatial scale, and assuming a similar situation for most of the people in this hypothetical Neolithic world, then she can exchange something (ideas, pottery, trade items) with virtually anyone in the network in just a few steps, by making use of connections at the appropriate spatial scale. In a small world, a Neolithic woman in the Rhine valley might obtain a piece of *Spondylus* shell from the Black Sea coast, having passed only between a half dozen hands (including the crucial long-distance trader in a canoe), whereas down-the-line trade would have required it to pass through hundreds of people's hands—and probably never make it that far. The way to identify prehistoric small-world networks of trade will require artifact sourcing, though chemical sourcing methods or identification of manufacturer's seals or stamps on traded items. However, certain prehistoric exchange networks have already been represented explicitly enough (Wright and Johnson 1975:fig. 5) to determine whether they fit the small-world criteria of short path length and high clustering coefficient.

Small-world networks may even apply to the rise of early state societies. In the Indus valley local trade networks developed around each polity during the Regionalization era (5500–2600 B.C.), but by the Kot Diji phase (2800–2600 B.C.), weights and measures, seals, pottery styles, and other technologies appear in the same forms over an area larger than half a million square kilometers, and by the Integration era (2600–1900 B.C.) these items were fully standardized (Kenoyer 1995, 1998). This state formation apparently involved the emergence of a small-world network, brought about initially by the long-distance trade of prestige items and raw materials. Because the largest centers were connected to a high number of smaller towns in this trade network, it was vulnerable to the decline of any one of its major sites. After 1900 B.C., the Indus valley experienced a de-urbanization back into more regionalized polities (Possehl 1997). Interregional trade suddenly collapsed at many different centers, such as Harappa, Lothal, Kuntasi, and Dholavira (Possehl 1997; Kenoyer 1998). In this way we might see the decline of the Indus civilization as the dissolution of a small-world network, through the severing of cross-network ties, into a regular, clustered network. Again, like the corporate models discussed above, the topic of small-world networks and early state emergence is waiting to be explored in detail.

Scale-Free Networks

One of the hypotheses for what underlies the ubiquitous power-law distributions discussed above is a special, orderly class network called the scale-free network (Barabási and Albert 1999; Newman and Watts 1999; Albert et al. 2000; Albert and Barabási 2002; Barabási 2002). These networks have a power-law distribution of the number of connections to each node (Adamic and Huberman 1999; Barabási and Albert 1999; Amaral et al. 2000). The best-studied scale-free network is the network of Internet web pages, which is scale-free because the number of links to each site is power-law distributed (Huberman et al. 1998; Huberman and Adamic 1999; Albert et al. 1999, 2000; Broder et al. 2000). Perhaps easier to visualize, a scale-free network is like the hub system run by a major airline (figure 15.7), such that the number of connections from each airport is a power law (Bentley 2003:fig. 2.2). Through the ingenious technique of tracing modern human travel through the flow of marked bank notes (cash), Brockmann et al. (2006) recently demonstrated that modern human travel distances are characterized by a power law, with most trips being short, but the occasional long-distance leap contribution to a scale-free (and also small-world) human travel network.

<Figure15.7 a–b>

A simple mathematical model of their scale-free growth of a network of indivisible agents follows the description of Barabási and Albert (1999), in that (1) the population of agents grows and (2) new connections continually made within the network are preferentially attached to already well-connected agents. As the network grows, each agent acquires more attributes at a rate proportional to what it already has, which is again the rich-get-richer phenomenon. For example, when an airline creates a new flight, it is much more likely to involve a stop at O'Hare (Chicago) than in Boise, Idaho. Similarly, the larger the size of a corporation, income of an individual, or number of links to a website, the faster that quantity tends to grow. In the case of the Internet, several studies have confirmed that both growth and preferential attachment are necessary for a realistic model (Jeong et al. 2003; Yook et al. 2001; Albert and Barabási 2002).

Despite its success in replicating the power-law distribution of connections among network nodes, the original scale-free growth model of Barabási and Albert (1999) is inadequate in several ways to explain real networks. Perhaps the most obvious problem with strict preferential attachment is that only the oldest agents dominate, while new agents entering the network without connections have no chance to succeed. Clearly, this is inadequate to account

for the overnight success of a new website, the rise of an entrepreneur, or a highly influential theory by a previously unknown scientist. One potential solution to this problem is to assign fitness values such that each node acquires new connections in proportion to its fitness as well as the number of connections it has (Bianconi and Barabási 2001), which allows newcomers with some outstanding quality to become highly connected (successful) over time.

Another problem with the Barabási and Albert (1999) model is that the network becomes less and less clustered as it grows (Albert and Barabási 2002:fig. 24), and is thus not a good model for networks that exhibit both small-world and scale-free qualities. The Internet as a small-world is a case in point, because any two web pages within this network of hundreds of millions of sites are connected by a limited number of steps, averaging about sixteen clicks between any two web pages (Albert et al. 1999; Broder et al. 2000). Airplane travel is also a small world in that rarely are any two airports in the world more than three stops apart, thanks to major hubs like O'Hare or Amsterdam. To tackle this problem, Barabási et al. (2002) built on the fitness model by allowing the network to grow almost like a fractal tree. Picture a branching river network with both a scale-free structure (big branches lead to many smaller branches, which lead to many smaller branches, and so on) as well as a clustering among nearby branches. Fractal geometry may underlie many complex systems (Strogatz 2005), as discussed below.

Although network theory has offered many new insights, including phenomena that are unique to networks as compared to other dynamical systems (Stewart 2004; Barabási 2005), it can also add unnecessary complication when a simpler explanation is available. For example, the preferential attachment rule for scale-free networks is really no different from the multiplicative growth models discussed above, or even simply the two preconditions that the anthropologist John Bodley (1999:609) has posited for wealth inequality in Washington State, one being "high rates of growth in population, property transactions, and new construction," and the other being that this growth "generate public costs that must be shared by all taxpayers." For this reason, the application of the scale-free network model on such quantities as urban land values (Andersson et al. 2003) appear to be forcing the model where it is not necessary. In fact, many of the subjects of recent network analysis—such as web links, Hollywood actors, and scientific collaborators—could just as easily be thought of as ideas that are copied among individuals (Bentley and Shennan 2005). The neutral or random copying model (see Collard et al., chapter 13; Neiman 1995; Bentley et al. 2004), in which ideas are copied—with occasional innovation—from one individual to another, produces a power-law distribution without requiring any imposed rules such as preferential attachment. In the random copying model, the rich-get-richer effect emerges naturally because the more popular a variant is, the more likely it will be copied again, becoming even more popular. Also, overnight success, which requires add-on rules for the scale-free network model, causes no difficulty in the random copying model, whereby any new variant might become highly popular by chance alone (Bentley and Shennan 2005). While we should recognize the exciting potential of network theory, we should also try not to overlook more traditional solutions to similar questions.

Punctuated Change

As open, nonequilibrium systems, human societies are also prone to instances of abrupt change, often triggered by seemingly inconsequential events, similar to a *phase change* in physics (Castellano et al. 2000; Ball 2004: 99–120). The idea of abrupt change in prehistory goes in and out of fashion in archaeology, and recently abrupt change and catastrophes have been reconsidered as shapers of prehistory (Maschner 2000; Rosenberg 1994; Rowley-Conway 2002;

Weiss 1993; Diamond 2005). At the same time, the idea of equilibrium (though criticized above) can make sense, as societies often do remain essentially the same, at least for a while. To accommodate these opposing tendencies, we might hypothesize that human societies undergo a *punctuated equilibrium* mode of change (Eldredge and Gould 1972; Bronk-Ramsey 2003), that is, from stasis to rapid change or collapse, stasis again, and so on. Large effects need not be perpetuated by overwhelming causes—one shot can start a war, one invention may transform a society, and one bad crop yield might collapse it. This is why the archaeology of specific events, a long-running topic of debate (Binford 1985; Gould 1985), can have great relevance when it is possible to do it (Gould 2005). As an example, the Thule migration across the Arctic about A.D. 1100 was facilitated by their adoption of the Asian recurve bow, armor, and other related technologies, technologies whose rapid spread between A.D. 1000 and A.D. 1200 changed the social and political worlds of most Native American peoples from the Bering Strait down the west coast of North America, the Great Basin and Southwest, and eventually the Mississippi basin (Maschner 2000).

A popular book on the way things change quickly is *The Tipping Point*, by Malcolm Gladwell (2000), but punctuated change was the interest of archaeologists who adopted catastrophe theory (Thom 1975) over twenty years ago (Tainter 1996). One proponent was Renfrew (1978; Renfrew and Cooke 1979), who showed how abrupt transitions could take place in systems with several possible equilibrium (metastable) states in which multiple variables affect benefits in contradictory, nonlinear ways. Renfrew (1978) demonstrated how slow changes in external parameters (such as climate), by causing people to adapt by small modifications of behavior, could lead them to a bifurcation point, where it is suddenly necessary to make a drastic change in order to maintain the optimal behavior (Ormerod 1998). Something may function less and less well for a while, until suddenly one day it is abandoned for something else. This may have occurred in prehistoric Europe where during the generations that Mesolithic hunter-gatherers traded with nearby Neolithic farmers, the environment or the social relationship changed such that at some point, hunting and gathering lost its original benefits, and an abrupt shift to farming finally occurs (Renfrew 1978; Zvelebil and Lillie 2000).

Chaos Theory

Like systems theory, catastrophe theory is based on the idea of transitions between equilibrium states; the transitions occur gradually in systems theory, and abruptly in catastrophe theory. However, what if there is no equilibrium state for the system to find? It is possible for us to define a system in a perfectly deterministic way, by defining all the rules, and yet when the system is set in motion, it is totally unpredictable. This is the phenomenon of *chaos*. A deterministic system is chaotic if an infinitesimal change in initial conditions leads to an entirely different series of events.

As engagingly described by Gleick (1987), chaos was discovered with the realization that deterministic equations, when repeatedly applied, can lead to results that are so sensitive to the initial values of the parameters as to be unpredictable. To show how this can happen, consider the logistic map, which is described in detail by most textbooks on differential equations. Suppose that we wish to model the population of algae in a pond. There are two tendencies acting on the population level, one for the existing algae to multiply, and the other for some algae to die off as the population reaches the carrying capacity of the pond. A reasonable, simple equation for the population of the pond P_t is then

$$P_t = AP_{t-1}(1- P_{t-1}), \qquad \text{eq. (2)}$$

where A is a constant greater than one, P_{t-1} is the population of the pond in previous year, and the population varies from 0 (no algae) to 1 (pond at capacity). To arrive at the population in successive years, eq. (1) must be *iterated*, that is, this year's population is plugged into the equation to get next year's population, and the result plugged in for the year after that, and so on. This is simple enough to be done on a spreadsheet.

This equation, which can be represented as a simple box model (figure 15.8a), has become a classic example of how iterating a simple equation can lead to chaos. To be specific: it turns out that if A in eq. (1) is between 1.0 and 3.0, the pond converges upon a stable population, called an "attractor," which could be seen as the result of an equilibrium process.

However, attractors are only one aspect of the logistic map, if we raise A in eq. (1) to just above 3.0 and the population of the pond begins to oscillate from year to year. At first the cycle is between two values, but as A is increased the cycles include more and more values until finally the cycle never repeats itself and the population is chaotic. In this chaotic regime, it is impossible to detect a pattern from year to year, and long-term prediction is impossible: this is what is meant by "sensitivity to initial conditions." Figure 15.8b shows, for A = 3.8, what happens when the model is run for the two slightly different starting values of P_0. After about twelve model years, the populations diverge and soon become totally different, not just in value but in their patterns of variation over time. This is the essence of chaos; two nearly identical stating points lead to two completely different trajectories in time, such that the dynamics are fundamentally unpredictable.

<Figures 15.8a–b>

The relevance of chaos and the stability of prehistoric societies have been noticed by archaeologists before (see Bintliff, chapter 10; Bintliff 1999, 2003; McGlade 1995, 2003; McGlade and van der Leew 1997). Chaos theory demonstrates why the debate between post-processualists and processual archaeologists—between uncertainty and positivism—is based on a false dichotomy. This is because for any given state system, there is only one possible history, but even when the dynamical rules of that system are *exactly* defined, it can be impossible to predict its future. No matter how well we may know the state of a society at present, we cannot predict very far into the future because whatever tiny uncertainty we have about the present grows geometrically with how far into the future we want to predict. Reversing this, by trying to reconstruct the past from evidence available in the present, there can be an infinite number of possible histories because we do not *perfectly* understand the present state. This has real implications for archaeological interpretation. Given the chaos that can be created with the simple box model in figure 15.8a, we should be skeptical of box model representations for prehistoric socioeconomic systems with dozens of boxes and arrows, since implementing such a model could not in any sense be predictive, or even explanatory. The dynamics of such box models are highly variable and dependent on the number of boxes, number and configuration of inputs and outputs, and so on (Hannon and Ruth 1997).

The Edge of Chaos: NK Landscapes and Self-Organized Criticality

Catastrophe and chaos theory demonstrated how even deterministic equations for keeping track of one variable, such as population, can lead to abrupt and/or unpredictable changes. So what happens if there are many variables to keep track of all at once? This is the case with the behavior of individuals, as opposed to the average behavior of a group. The problem of predicting a system of interacting agents, in which each agent's actions depend on those of other agents, is what Stuart Kauffman (1993, 1995) was considering when he developed his NK landscape. The NK landscape is a simple model of N agents, interconnected in a simple grid network such that each agent is randomly connected to K other agents. A tiny bit of "personality" is added to the agents, in that the interactions between each agent and its K neighbors can be made to be cooperative, competitive, or a mixture of both. Each agent, therefore, has a unique set of conditions governing its behavior, because its actions not only depend on the interaction rules assigned to it but also on its reactions to the K other agents in its communication network. Since the actions of the neighbors change continually, optimal strategies in the present moment may not be what they were in the previous moment because they depend on the previous actions of other agents. This has been named the Red Queen effect (Van Valen 1973), after the Lewis Carroll character, because the agent must run faster just to stay where it is—keep changing just to stay competitive.

Kauffman (1995, 2000) showed that the outcomes of these networks depend on agent strategies and also on N and K. If the agents are only moderately connected (lower values of K), then by adjusting their strategies accordingly, agents can all adapt fairly easily. However, as things become more interconnected (higher values of K), agents must choose either to make small adjustments to optimize their current strategy, or undertake major, risky changes in order to seek a better long-term strategy. When the network is completely interconnected (K = N - 1), each agent has about as many favorable as unfavorable interactions, highly favorable strategies may simply not exist, and a directed search for improvement is no better than random guessing (Kauffman 2000:201–202). In the years since the NK model was introduced, one of the major questions has been how agents can search for better strategies, especially when stuck on a localized fitness peak—picture a mountainous landscape where the height of each peak represents the benefits or fitness of a strategy (Dennett 1995; Axelrod and Cohen 1999; Erwin and Krakauer 2004). Schultes (2000) provides an excellent example when he compared politics to a highly connected NK landscape, in that all the competing interests that the U.S. presidential candidates are compelled to satisfy (i.e., high K) was to blame for their mediocre compromises on policy issues.

In archaeology, Kohler et al. (2000) used the NK model to explore what may have been the prehistoric effect of increasing the number of households, clans, or communities (i.e., increasing N), along with changes in the number of exchange connections (K) between these units. Analogy with the NK model suggests that Prehispanic societies that became too interconnected (high K) performed poorly in terms of exchange and decision making due to the interconnectivity of these systems. Kohler and colleagues argued that when plaza pueblos appeared at Pajarito plateau in New Mexico about A.D. 1275, the number of households (N) increased but the interconnections changed such that the connections of each household, K, was kept fairly constant. Through plaza pueblo site organization, "the residents tried to maintain the older pattern of high connectivity within their modules (kin groups, roomblocks) and sparser connectivity between" (Kohler et al. 2000:381). In this way they avoided what Kohler et al. (2000:376) call the "high K complexity catastrophe."

One of the promising results of Kauffman's NK model was that it produced avalanches of change whose sizes were distributed by a power law. Similar power-law distributions had been observed for the sizes of natural, cascade-style events, such as forest fires, landslides, and

earthquakes (Turcotte 1997). In Kauffman's NK landscapes there existed a regime for certain values of N and K, in which the system hovered between an ordered regime of stasis and a chaotic regime of unpredictable change. By analogy, Kauffman reasoned that natural complex systems of many interacting components evolve on their own to a state "poised at the edge of chaos" (Kauffman 1994). In physics, Per Bak and his colleagues (Bak et al. 1987) called this state "self-organized criticality." Whereas in the chaotic state, a small perturbation to the system triggers a cascading sequence of interconnected events, in a self-organized critical state, some perturbations only trigger small changes, while others can cause an avalanche of consequent events (Bak and Chen 1991; Bak 1996; Turcotte 1999). It was as if self-organized critical systems were tuned by an invisible hand to the point where chain reactions occur at all size scales, from insignificant perturbations to avalanches that sweep through the entire system.

The reason they are called avalanches is that self-organized systems are exemplified by a sand pile (Bak 1996; Jensen 1998:14–16, 92–99). If dry sand is poured onto one spot, a pile will soon form that eventually reaches a critical slope, such that sand slides occur on its sides. In this critical state, one or two grains can trigger a sand slide. The pile hovers between two regimes—sand slides that reduce the slope of the pile keep it out of the chaotic regime of runaway avalanches, while the continual pouring of sand (open system) keeps it from stasis. It turns out that in this self-organized critical state, the distribution of sizes of avalanches on the sides of the sand pile is a power law, meaning that change occurs at all size scales and frequencies, from infinitesimal and often, to massive but rare, and everything in between, all as part of the same elegant power-law distribution function.

The analogy between sand piles and real-world complex systems is appealing. Remove a grain in a sand pile and others will fall, or as one commodity fails in the market so do products related to it (Lux and Marchsesi 1999). Many inspired by the theory have suggested that self-organized criticality may govern changes in society and culture (Gell-Mann 1994; Kauffman 1995; Bak 1996; Buchanan 2001), technological evolution (Arenas et al. 2000; Kauffman 2000; Bentley and Maschner 2003b), and has been applied successfully to understanding the stages of lithic reduction (Brown 2001). The only trouble with the self-organized criticality theory is that it is mainly a description of a dynamic state rather than a truly causal explanation. So, while the model of self-organized criticality might be favorably compared to records of historic pottery styles as evidence of interconnected avalanches of change (Bentley and Maschner 2001), this is not truly an explanation for how and why those changes occurred. Until this happens, archaeologists may remain reserved about the theory of self-organized criticality (Pruecel and Hodder 1996:28; Renfrew and Bahn 1996:473).

Information Cascades

Despite the lack of clear explanation in the theory of self-organized criticality, the observed phenomenon is real—natural and social systems do self-organize into states characterized by a power-law distribution of event sizes. Strogatz (2005) asks:

> Why do so many of nature's networks live on a razor's edge? Have they self-organized to reach this critical state (Bak et al. 1987), perhaps to optimize some aspect of their performance, or have they merely followed one of the manifold paths to power-law scaling (Newman 2000), full of sound and fury, signifying nothing? (Strogatz 2005:366, citations in original)

Fittingly, since it was introduced by Bak et al. (1987), the concept of self-organized criticality has spread through the journal literature like an interconnected avalanche (Bentley and Maschner 2000). By the end of 1999, the distribution of the number of citations these papers had acquired a power-law form (Bentley and Maschner 2000). In other words, the seminal paper by Bak et al.

(1987) was cited the most, followed by the papers that it cited, followed by the spin-offs of those papers, until finally the most recent papers on comparatively minor aspects of the theory, which still cite Bak et al. (1987) yet they themselves are hardly cited at all. Similar power-law distributions are found for prehistoric ideas, namely, decorative motifs on prehistoric pottery (Bentley and Shennan 2003; Bentley et al. 2004; Shennan and Bentley 2006). Schiffer (2005) recently proposed a similar model for the invention of complex technological systems, such as the telegraph in the nineteenth century, which involves a punctuated series of invention cascades, as people compete to develop various interrelated aspects of the invention. Bentley and Maschner (2000, 2003b) argued that such cascades or avalanches could be envisioned as a growing tree: at the base is the seminal idea (trunk), which gives rise to several spin-off ideas (large branches), which in turn give rise to other, less significant (or more specialized) spin-off ideas (smaller branches), and so on, until another new seminal idea starts a new avalanche (new tree). This tree of ideas could be seen growing in time and spreading into more and more remote corners of contemporary culture. If the lengths of the branches were drawn in proportion to how influential (i.e., how often copied) each idea was, the depiction might take on a *fractal* form (figure 15.9). Like a braided river, which looks the same on the massive scale of the Mississippi and all its tributaries to the small-scale braided rivulets of water draining through the sand on a beach (Turcotte 1997), a fractal is said to be *self similar* (or more technically, *self-affine* if not exactly identical at all scales). Comparing the evolution of ideas to a piece of broccoli (another fractal shape) may seem crazy, but it isn't. It was recently demonstrated that the Internet has quantifiably fractal properties (Song et al. 2005), which has led to the consideration that fractals may underlie a new architectural law for complex systems (Strogatz 2005).

<Figure 15.9>

The concepts of fractal properties of information spread and network interactions are quite closely related (Vandewalle and Ausloos 1996, 1997; Barabasi et al. 2001), and this can be demonstrated through modeling of information cascades. Watts (2002) explored how network structure affected the size of the information cascades that swept across it, through the interconnected agents. With each agent being a zero at the start, one agent was given an idea by switching it to a one. At the next time step, another randomly selected agent would be switched from zero to one. These randomly selected agents were the innovators. To represent the behavior of the adopters, agents were assigned threshold values between 0 and 1 such that if the fraction of connected neighbors with the idea was greater than its threshold, it would switch too. If an agent's threshold was 0.85, for example, then at least 85 percent of its direct neighbors would have to adopt the new idea before it would adopt the idea as well. Each time an agent switched, it increased the fraction of idea holders for all its surrounding agents, and hence may cause one of them to switch, and so on, leading to a cascade of a size defined as the number of agents that switch. As expected, cascades occurred more readily through a network of agents with low thresholds than high thresholds. In fact, Watts (2002) found that as the average threshold is increased, a point is reached where system-sweeping avalanches become practically impossible, with each avalanche ultimately being curtailed by particularly stubborn agents.

Watts (2002) also found that a sparsely connected, scale-free network was subject to cascades of all sizes (through a power-law distribution), at least up to the limit of the largest interconnected cluster within the network. However, as random connections were added to the network until it was highly interconnected, the size of the cascades became limited (via an

exponential distribution), such that small changes built up until suddenly a massive cascade occurred among all the yet unchanged agents at once. The reason for this was that most agents in a sparsely connected network have only a few direct neighbors, and are therefore more susceptible to being influenced by a single neighbor. By contrast, each agent in the highly connected network was connected to many others and is thus less likely to be swayed by a change in a single neighboring agent (Watts 2002:5770). There is a similarity here to the NK landscapes discussed above; as agents are made more highly interconnected, they become overwhelmed with information and less likely to make a bold decision, so to speak.

This leads to a natural question: What happens when agents have a variety of different reactions to their information? The models discussed so far treat agents as identical. Watts, however, recognized that variation among agents not only makes the model interesting, but it is *essential* for the model to represent certain realistic aspects of the real world. Instead of modeling all agents with the same threshold, Watts (2002) in his second experiment randomly assigned a range of different thresholds to the agents, such that some were now innovators, others early adopters, and others late majority and so on, meaning that different agents had different amounts of peer pressure. Watts (2002) found that as these agents were made more heterogeneous—with a wider variety of thresholds—system-sweeping avalanches became more likely. Watts (2002) reasoned that among heterogeneous agents, there exists a better mix of early adopters (low threshold) to get an avalanche started and early and late majority agents to keep it going.

Agent-Based Modeling

Watts's (2002) discovery that heterogeneity among his agents led to qualitative differences in his model results is profound. Moving from simple models of generic agents—such as sand grains, NK landscapes, or nodes and lines in a network—to simulation models in which the agents themselves are varied and complex, enters the realm of *agent-based modeling*. As Costopoulos describes in chapter 16 of this volume, agent-based modeling allows an archaeologist to describe a prehistoric human society with an open, nonequilibrium model, which can be run again and again, to see whether any general states tend to result from certain combinations of agents, agent rules, environments, and initial conditions (Axtell et al. 2002; Bankes 2002a; Bonabeau 2002). Agent-based approaches provide the opportunity to combine many formerly-competing bodies of archaeological theory described in this volume, including the multiple narratives of post-processualism (see Shanks, chapter 9), the hypothesis testing of processualism (Watson, chapter 3), ecology (Yesner, chapter 4), and agency (Gardner, chapter 7). Agent-based modeling even has heavy philosophical implications (see Koerner and Price, chapter 21), as physicists now are seriously considering the possibility that our own world could be a simulation (Barrow 2003)!

Agent-based modeling (ABM) of complex adaptive systems involves computer simulation of the actions of heterogeneous agents that populate a landscape of simulated resources. Made possible by recent accelerations in computer processing, agent-based modeling allows the testing of hypotheses for complex systems in the social sciences (Gilbert and Doran 1994; Gilbert and Conte 1995; Conte et al. 1997; Gilbert and Troitzsch 1999), including archaeological studies of hunter-gatherer subsistence (Lake 1999) and late prehistoric settlement (Kohler et al. 1999; Axtell et al. 2002). An agent is something with the ability to interact purposefully with its environment that, importantly, includes other agents. Agents can be defined at any scales such as individual potters, households, villages, or any other unit. These agents possess attributes such as life span, vision, movement capabilities, and consumption and storage capabilities and can represent such real-world entities as households, clans, or villages (Dean et al. 1999). The basis of ABM is that each agent acts based on its own local information, with at least some dependence on what other nearby agents are doing, and what they have learned about their world over a series of "time steps." In early models, the rules by which agents acted were often based on ethnography and optimal foraging theory (Kohler and van West 1996; Read 2002).

In successive time steps, the general sequence of an agent-based computer model is (1) each agent acts according to its rules and local environment, (2) the world is changed according to the sum of all agent actions, (3) agents react to their new environment, and so on. Importantly, the network in ABM is not predetermined, as agents are allowed to create the network themselves through their collective interactions. Thus, while the network models discussed above are more predictive, ABM is potentially more realistic, contingent, and surprising. In this context, game theorists have traditionally examined games such as the Prisoners Dilemma (Axelrod 1984, 1997) and looked for "evolutionary stable strategies" (much like equilibrium) among the agents who play different strategies. With ABM, it is possible to discover nonequilibrium dynamics that would be impossible to predict through differential equations, including chaotic outcomes from a simple two-person game (Sato et al. 2002), the transformative effects of adding memory to the agents (Andersen and Sornette 2003), or the results when the agents compete for limited resources on a small-world network (Anghel et al. 2004; Bentley et al. 2005).

A typical application is exemplified by Lake (1999), who used agent-based modeling to address the question of whether the first foragers on the island of Islay (Southern Hebrides) were driven to explore the island by their search for hazelnuts. Using available data such as pollen records and modern soil maps, a GIS model was constructed for the climate, vegetation, and soil distribution of the island around 7000 B.P. (Lake 1999). This includes a model distribution of hazelnut trees. Each agent in Lake's model represents a family of four foragers. Although Lake (1999) includes many other variables in their decisions such as risk taking, foragers in the model basically seek nearby GIS cells with more hazelnuts than the one they currently occupy. These agents remember what they have seen and periodically share information with each other. The agents drop artifacts as they use them. Because the model results did not match the archaeological distribution of Mesolithic sites on Islay, Lake (1999) concluded that hazelnuts were not the primary motivation for foragers in occupying the island.

Many of the leaders in the application of ABM in archaeology have used it to model Anasazi village formation in the American Southwest (Kohler et al. 1999; Dean et al. 1999; Axtell et al 2002). The paleoenvironmental landscape for these Anasazi models makes use of particularly detailed records of dendochronology, geomorphology, palynology, and archaeology from the region. By populating this landscape with artificial agents (representing households), the output of the ABM compares quite well to the actual history of the Anasazi from about A.D. 800 to 1300 (Axtell et al. 2002). As for future applications, Bogucki (2000, 2003) has argued that the Neolithic spread of agriculture across north central Europe can be seen as the evolution of a complex adaptive system, soliciting an ABM approach.

Agent-based modeling appears to be revolutionary in the social sciences for three reasons (Bankes 2002a; Bonabeau 2002): (1) ABM does not require the old assumptions of equilibrium, normality, and linearity, the problems with which have been discussed above; (2) ABM demonstrates emergent phenomena; and (3) compared to generalizing mathematical approaches, ABM is a more natural way to describe a social system because it replicates the actions of agents. Since this is the same level that we observe the real world, ABM allows the incorporation

of a much broader array of sociological and anthropological data. Axtell et al. (2002) were able to bring their Anasazi ABM even closer to the actual history by adding more heterogeneity to their agents by varying such parameters as age at death, age range of fertility, and group fission probability among the individual agents. Agent-based models can be wonderfully detailed and complex, and as such can be realistic in the general way that events play out. However, there is always the danger of adding too much detail, which not only may fail to bring the model any closer to reality, but may also make the modeler's desired results inevitable (Inchiosa and Parker 2002). Furthermore, ABM should never be mistaken for a reproduction of reality, and a correspondence between model results and observed data always suffers from a lack of equifinality; that is, it provides many possible explanations rather than a single, definite one (McGlade 2003). It is commonly remarked that there are more possible games of chess than there are atoms in the universe, so surely one game or even hundreds of games do not tell us how the next one will go. The same can be said for agent-based models. We must be careful to regard a good ABM as explanatory through its analogy with reality, but not predictive. Since any system we seek to model by computer is itself a symbolic representation of a real process, merely comparing the model to the simplified data as a scientific "test" is self-referential (Baker 1999).

Conclusion

While the postmodernists acknowledge the success of natural sciences such as physics, they see much greater, even hopeless difficulty in explaining complex open systems like brains, evolution, and ecology (Hesse 1995). Yet these difficult phenomena are just what complexity theory attempts to tackle. As Bintliff (1997; also chapter 10 of this volume) argues, complexity science brings past and present studies together by integrating the culture-historical approach, which stresses irreversible histories, with the natural history approach, which stresses cyclic processes. Recent advances in computer simulation are the reason reversible and historical processes can be observed together, as the number of calculations needed for agent-based models was simply not possible before modern computing (Low 2000). Without seeking to predict the exact trajectories of complex systems, the goal of complexity science is to understand their emergent properties and the effects of changes in features of the system. Agent-based models can be tinkered with and rerun many times. Kohler and Van West (1996) borrow from ethnoarchaeology to evaluate some of their model assumptions, such as the assumption that the household is an appropriate unit of analysis and that households share with neighbors when productivity is high. Comparison of emergent properties of an agent-based model to these ethnoarchaeological assessments in the real world indicates whether or not the operating model rules are on the right track.

One of the major lessons of complexity theory is that interactions between people are at least as important as objective constants defined with respect to an external environment. In economic theory, complexity theory (econophysics) challenges whether such sacred concepts as rationality, utility maximization and optimal behavior are even valid assumptions (Keen 2003; Ormerod 1998, 2005). Cultural evolution is not restricted to parent-child transmission. As Neff (2000:427) recently pointed out, one of the weaknesses in evolutionary archaeology is that "major changes in material culture, many of which would leave an obvious signal in the archaeological record, very often take place in less than one human generation . . . Since cultural transmission does not require biological reproduction, the latter need not enter the picture at all." For this reason, the complexity approach invites us to modify approaches that focus almost exclusively on vertical (parent-child) cultural transmission and hierarchy, to those that allow horizontal (between unrelated contemporaries) and heterarchy (Crumley 1995).

Finally, complexity approaches are useful in the real world. Among many examples, Bonabeau (2002) and Axelrod and Cohen (1999) use the insights of complexity theory to guide business management for the modern economy. Agent-based modeling has lead to an insight in crowd control—modeling the herding instinct from the individual agent's perspective has lead to a better exit design for a smoke-filled building (Helbing et al. 2000). Other examples include the application of ABM to such social science topics as public policy (Carley 2002; Bankes 2002b; Lempert 2002), social domination by a central authority (Cederman 2002; Epstein 2002), crowd control (Helbing et al. 2000), marketing and the diffusion of new technology (Arenas et al. 2001; Guardiola et al. 2002; Bonabeau 2002), and game-theoretical approaches to human organization (Macy and Flache 2002; Danielson 2002).

The influences of complex systems approaches on large, multidisciplinary research projects have been substantial and are now integrated into modern archaeological research. The Biocomplexity in the Environment research program at the U.S. National Science Foundation was set up in order to investigate the complexities of ecosystem dynamics. "Biocomplexity refers to the dynamic web of often surprising interrelationships that arise when components of the global ecosystem—biological, physical, chemical, and the human dimension—interact. Investigations of Biocomplexity in the Environment are intended to provide a more complete understanding of natural processes and cycles, of human behaviors and decisions in the natural world, and of ways to use new technology effectively to observe the environment and sustain the diversity of life on Earth" (NSF 03-597). The program specifically required that researchers take into account (from NSF 01-34):

- Thresholds and nonlinearities in ecological and social systems, emphasizing theoretical and empirical research linking human and biogeophysical processes to ecosystem services and other forms of natural capital
- The influence of future patterns and events on the demand for and provision of natural resources, ecological and geophysical services, including interdisciplinary work to improve forecasts across spatial and temporal scales
- Patterns and legacies of human settlement, migrations, urban development, ecological succession, and climate on land use and land cover
- Model development and testing for a variety of disturbance scenarios, including alternative treatments of uncertainty
- The role that access to scientific information, or the lack thereof, plays in environmental justice, and the most effective methods for disseminating scientific information to traditionally disenfranchised groups."

Under the subheading of dynamics of coupled natural and human systems, a number of multiyear research projects were awarded including several led by archaeologists. These include Tim Kohler's project in the American Southwest, Patrick Kirch's project in Hawaii, and more recently Ben Fitzhugh's project in the Kuril Islands and Herbert Maschner's project in the eastern Aleutian Islands, among others. Providing support ranging between $1 million and $2 million, these projects allowed archaeologists to integrate intensive complex systems modeling with data from archaeology, anthropology, ecology, history, geology, climatology, oceanography, and other disciplines in ways not envisioned in the past. Further, because these

data are generated at multiple spatial and temporal scales with varying degrees of fuzziness or accuracy, only complex systems approaches have the methods to handle such disparate problems.

Archaeologists are increasingly interested in complexity science because it is explicitly for the study of systems of interacting agents, which is what all human societies are (Kohler 1993; McGlade 1995; Kohler and Van West 1996; Haas 1998; Bintliff 1999; Kohler et al. 1999; Bogucki, 2000; Bentley and Maschner 2001; Axtell et al. 2002). In the United States, questions in archaeology are regularly being addressed at the Santa Fe Institute, and in Britain there is the Centre for the Evolutionary Analysis of Cultural Behaviour (UCL), where one focus is on complexity science applications for archaeology. Reviews of this field are growing in archaeology and include Bentley and Maschner's *Complex Systems and Archaeology* (2003). Outside of archaeology, an exhaustive, accessible tome on how complexity theory applies to human societies is Phillip Ball's (2004) *Critical Mass,* which should fascinate anyone who finds this less detailed chapter interesting. In addition, those interested more specifically in complex networks might try *Six Degrees*, by Duncan Watts (2003), or a recent review on networks and social theory by Evans (2004). Those interested in how complexity theory has transformed economic theory might try *Why Most Things Fail*, by Paul Ormerod (2005).

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