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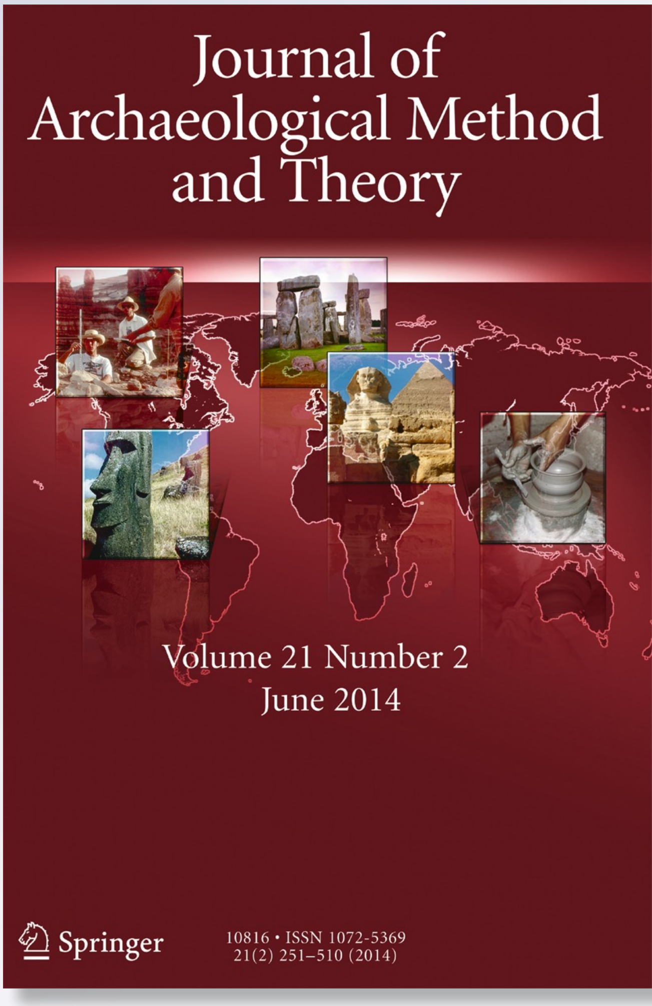

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Abstract Social complexity has long been a subject of considerable interest and study among archaeologists; it is generally taken to refer to human societies consisting of large numbers of people, many social and economic roles, large permanent settlements, along with a variety of other marker criteria. When viewed from a more general complex systems perspective, however, all human societies are complex systems regardless of size or organizational structure. Complex adaptive systems (CAS) represent systems which are dynamic in space, time, organization, and membership and which are characterized by information transmission and processing that allow them to adjust to changing external and internal conditions. Complex systems approaches offer the potential for new insights into processes of social change, linkages between the actions of individual human agents and societal-level characteristics, interactions between societies and their environment, and allometric relationships between size and organizational complexity. While complex systems approaches have not yet coalesced into a comprehensive theoretical framework, they have identified important isomorphic properties of organization and behavior across diverse phenomena. However, it is difficult to operationalize complex systems concepts in archaeology using the descriptive/confirmatory statistics that dominate quantitative aspects of modern archaeological practice. These are not designed to deal with complex interactions and multilevel feedbacks that vary across space and time. Nor do narratives that simply state that societies are characterized by interacting agent/actors who share cultural knowledge, and whose interacting practices create emergent social-level phenomena add much to our understanding. New analytical tools are needed to make effective use of the conceptual tools of complex systems approaches to human social dynamics. Computational and systems dynamics modeling offer the first generation of such analytical protocols especially oriented towards the systematic study of CAS. A computational model of small-scale society with subsistence agriculture is used to illustrate the complexity of even "simple" societies and the potential for new modeling methods to assist archaeologists in their study.

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Introduction

Complexity has been a topic of interest to archaeologists since before Christian Jürgensen Thomsen's creation of the "three-age system" to group artifacts in the Museum of Northern Antiquities (now the National Museum of Denmark) into Stone, Bronze, and Iron Ages. What most archaeologists mean by complexity is social complexity, generally associated with large, dense populations and a suite of characteristics that include social hierarchies, socio-economic specialization, and urbanism (Adams 2001; Carballo *et al*. 2013; Cowgill 2004; Feinman 2011; Feinman 1998; Smith 2009). Given that human complex societies dominate the world today, understanding the origins and nature of this kind of complexity is indeed important.

But there is a different approach to complexity that can be applied to all human societies, regardless of whether they meet the criteria of social complexity: that of studying human social systems as exemplars of a broader phenomenon of complex adaptive systems (Miller and Page 2007; Mitchell 2009a). There is a long history to the idea of treating human societies as systems linked together by flows or exchanges of materials, energy, and ideas (e.g., Flannery 1986; Moran 1991; Rappaport 1971). In the broadest sense, systems are a collection of entities linked to one another in some way—ranging from closed and static like the molecules of a crystal (i.e., not requiring a continued input of energy to maintain the linkages), to open (i.e., requiring an external source of energy to maintain the system) and dynamic (i.e., changing through time) like the cells that together form a jellyfish. Complex adaptive systems (or CAS) are a class of open systems that share a number of special properties.

Complex Adaptive Systems

The following is a brief overview of the more salient concepts relevant to CAS; more comprehensive discussions can be found in (Barabasi 2012; Cowan *et al*. 1994; Henrickson and McKelvey 2002; Holland 2000; Lansing 2003; Mitchell 2009b; Mitchell 2006; Simon 1962; Strogatz 2001), and additional examples of the application of CAS concepts to archaeology can be found in (Bentley and Maschner 2003; Bernabeu Auban *et al*. 2012; Feinman 2011). CAS are found naturally as living organism and societies of organisms, as well as within human technologies (i.e., in complexly engineered systems like airliners). The components of CAS are organized into nested groups that can be represented as *structured networks* or *organizational hierarchies*; the more complex the system, the deeper the nesting of the groups of components. Multi-cellular organisms, like humans, are comprised of cells that themselves are made up of nuclei and organelles within the cytoplasm. We are not a blob of cells, however. Rather, the cells in our bodies are organized into organs that are connected into larger organ systems like the cardiovascular system. These, in turn, are linked together into the organic whole of our bodies. From a social perspective, this organization of nested groups can be seen as nuclear families within forager bands, and bands within regional macrobands; households within clans within chiefdoms; or individuals within craft guilds within towns within states.

This organizational structure has a number of important consequences. Interactions among components within one of the nested groups tend to be more frequent and stronger than interactions between groups at any level in the nested hierarchy. Cells of the heart interact more directly with other heart cells than they do with lung cells, even though both are part of the cardiovascular system. Cells of the cardiovascular system have more interactions with each other than they do with cells of the digestive system. Similarly, social ties between forager bands are generally weaker than those between the co-resident individuals and families within a band. Households have more frequent, direct interactions with other households in the same town than they do with households in other towns. As a result, groups that make up the nested hierarchies of CAS often can continue to function even when their linkages to other groups are broken. A heart can be removed from the body of one individual and transplanted into another, and continue to function as it did before. A town can lose its political connections with one state and be incorporated into another (e.g., due to conquest in war), and life can go on much as before. This property of stronger linkages within groups than between groups, and the ability of groups to operate semi-independently of their connections to other groups in a nested hierarchy is called *near decomposability*, and affects the way CAS develop and disaggregate.

As Simon (1962) illustrates with his fable of the two watchmakers, CAS tend grow "organically" as low level components are joined into groups, and these groups are joined into higher level metagroups. This organic process helps explain why past societies seem to evolve toward levels of increasing complexity—especially when seen from the backward-looking perspective of an incomplete archaeological record. Multi-level social hierarchy does not develop directly from autonomous households, but by combining social groups that already have simpler organizational hierarchies. CAS tend to disaggregate in reverse order to the way they evolve: the highest level groups become independent systems, disassociated from other groups, and which can subsequently disaggregate into their respective subgroups. For example, the western Roman Empire did not collapse into anarchy but decomposed into its administrative provinces. These administrative units often coincided with the territories of pre-Roman societies that shared social and political ties, conquered and assimilated by the expanding empire. Moreover, their boundaries resemble those of modern nations that make up the European Community today.

Because CAS components interact with other components in multiple dynamic ways, in variable frequency and intensity across the nested hierarchical organization, the scale and direction of change at the system-level is not necessarily proportional to the scale and direction of the phenomena that trigger it. Additionally, it is more the character of the *interactions* among components rather than their inherent characteristics that determines the behavior of a CAS at the system level. Sometimes, a CAS can absorb a great deal of perturbation and remain relatively unaltered; in other cases, a comparatively minor disruption can initiate a cascade of changes that fundamentally alter a complex system—and can even cause high-level linkages among components to break, resulting in "collapse." This *nonlinear* causality can make system-level behavior difficult to predict from properties of the components alone. In fact, complex systems often exhibit novel behaviors at the system level that are very different from anything exhibited by any components, a phenomenon called *emergence*. An example of emergence can be seen in our individual bodies, which can carry out behaviors that do not exist in any of our individual cells. Similarly, the combined actions of many people and their shared cultural knowledge construct jet airliners with alacrity, even though no single individual has the knowledge or skills to do so.

A key emergent property of CAS is their capacity for *computation*. Not only material and energy, but also *information* is transmitted among system components. CAS components and groups at all levels, from DNA to cities, can receive information about their surroundings, alter their behaviors in response to that information, and transmit information about their state to other components. That is, CAS components have *agency*. This agency can be mediated by chemical reactions, pheromones, or language and culture, and scales up through the hierarchical structure of CAS. Simultaneously, the cells of our immune system are responding to changing environmental conditions—receiving information about potential pathogens, attacking or not attacking another cell they encounter, and transmitting their state to other cells of the system to attract white blood cells to dispose of the pathogen (or not)—while we are responding at the level of an individual human to conditions of our internal immune system (e.g., through a fever and medical treatment) as well as to the biophysical and social environments in which we find ourselves. This ability to collect, process, and transmit information, and for system components to alter their behaviors on the basis of this information, processing allows CAS to *adapt* and maintain system-level integrity and function in changing internal and external environments.

Finally, with the exception of some technological systems, the organizational structure, interactions, computation, and emergence that characterize CAS are not imposed by some external force, but rather develop organically as a consequence of endogamous rules that govern the behavior of individual components. This tendency is often referred to as *self-organization*. Neither the development of a fertilized egg into an embryo into an individual, nor the evolution of life from single cells to multicellular organisms to social organisms is the result of an external guiding force, but the expression of internal rules governing the behavior of each individual component as it interacts with other components and other features of its environment over time. CAS and their particular properties are the emergent consequences of individual agency.

Applying a CAS Approach to Prehistoric Socio-ecological Systems

CAS concepts have considerable potential for contributing to understanding the dynamics of human societies and their interactions with the biophysical world. Several aspects should be particularly attractive to those who take a more holistic view of culture and society that emphasizes cultural/social drivers of change. These include the idea that social dynamics are driven by the practices of individual actors, who ascribe to a common body of knowledge but who make decisions contingent on the practices of other actors and the structure of social interactions, as well as biophysical characteristics of their environment. It is these actors whose endogamous cultural practices dynamically create and recreate the emergent social phenomena we see as societies.

Johnson (1982) points out the pervasiveness of hierarchies throughout human society, although they can take many forms and be transient or persistent, and notes that it is the social interactions and practices, more than the characteristics of individuals themselves that drive the emergence of social organization and its changes. The CAS nature of human society is consistent with the difficulty in characterizing it with simple, linear causal equations, and its frequent unexpected dynamics—and unintended consequences. A CAS perspective can help account for features that are fundamental to all human sociality and for the uniqueness of the myriad of expressions of that sociality in diverse societies across the world, past and present.

In spite of its potential as an explanatory framework for the sciences of human societies, applying a CAS framework in a meaningful way to the archaeological record is challenging to say the least. Viewing human societies through a CAS lens entails a focus on information flow, decision-making, interactions at multiple scales of organization, and non-linear dynamics in which individual agency generates system-level emergent phenomena—all of which are invisible in the archaeological record. We have no way to directly observe the dynamics of ancient human societies at either the actor or system level. It is a truism, but a trivial one, that every artifact is the product of individual agency. The material record of this agency is a disorganized, fragmentary, and often chaotic jumble of bits of objects produced by many different actors over long periods of time. What meaningful patterns that we can observe are indirect, material consequences of emergent phenomena, not agency nor emergence itself (Barton *et al*. 2012; Shennan 2002).

Certainly, we can weave CAS phrases into the narratives we infer from the archaeological record. But unless we change how we make sense of that record, CAS concepts will be little more than the most current of a stream of competing perspectives used to introduce what ultimately seem to be much the same kinds of narratives about the past—whether imagined under the banner of processualism, post-processualism, structuralism, post-structuralism, practice, historical ecology, or historicity.

The main challenges for archaeology in operationalizing CAS concepts in a science of long-term social dynamics are twofold. First, how can we systematically track and explain non-linear chains of causality that cascade from multi-scale interactions among individuals, groups, and the biophysical world up to the emergent level of socio-ecological systems? This is especially difficult when traditional analyses and narratives are inherently linear and our empirical data are static. New methods of data collection and representation can help reveal and characterize the spatially and temporally complex nature of the archaeological record itself (Altaweel and Wu 2010; Chase *et al*. 2012; Kvamme 2007). Also, some equation-based models of human behavioral ecology and related approaches can account for non-linear dynamics (Hooper *et al*. 2010; Turchin 2003). However, even these models have difficulty in adequately dealing with the kinds of multi-scale interactions of many spatially and culturally heterogeneous, independent actors.

Second, even with a firm understanding of the dynamics of human societies, how can we recognize and account for prehistoric socio-ecological CAS when key features are not preserved in the archaeological record? That is, what are robust proxies for CAS phenomena? While some preliminary examples of ways to identify CAS characteristics from the archaeological record are beginning to appear

(Bernabeu Auban *et al*. 2012), most archaeological treatises on CAS in archaeology have focused more on its potential than actual applications to date (Adams 2001; Bentley and Maschner 2003).

In part, meeting these challenges will require the development and application of robust theory about drivers and nature of long-term change in CAS. However, new forms of archaeological practice also can help begin to address the challenges of applying CAS approaches in archaeology. Especially when dealing with human societies as CAS, we can benefit from moving from inductive "reconstruction" of an unknowable past from an inherently poor archaeological record, to systematic experimentation and hypothesis testing, with validation (rather than inference) against the archaeological record. Of course, it is impossible to carry out real-world experiments with past human systems—or even with modern ones at the scales of interest to most archaeologists. However, computational simulation modeling offers a valuable protocol for combining anthropological and CAS knowledge to create experimental environments in which to explore non-linear causality in complex systems and generate results that can be evaluated against the empirical archaeological record.

At a general level, models are any abstract representations of real-world phenomena—including CAS. By *computational modeling* I am not referring any model that is operationalized in a computer, but to a particular kind of simulation modeling (i.e., modeling *formalism*) that involves the generation of multiple, discrete computational entities or *agents*, imbued with a set of *algorithmic rules* for sensing/filtering the environment, processing information and making decisions, and taking actions on the basis of those decisions. These entities are activated (or *instantiated*) to operate and interact in a virtual world without further control from the researcher. Such computational entities can take the form of a gridwork of cells in a *cellular automata* (CA), the *nodes* and *edges* (i.e., links) of a dynamic network, or agents in an *agent-based model* (ABM; also known as an *individual-based model* in ecology).

Simulations also have been applied occasionally in archaeology since the 1970s (see Gaines and Gaines 1997). With a few exceptions (e.g., Hegmon 1989; Wandsnider 1992; Wobst 1974), these have endeavored to replicate aggregate processes at the level of societies or populations, rather than the interactions of agents that create societies. While computational models can be used to simulate real-world processes in great detail (e.g., some manufacturing processes), their greatest potential for archaeology lies using them as environments of systematic, controlled, digital experiments in human social and socio-ecological dynamics (Bankes *et al*. 2002; Barton *et al*. 2012; van der Leeuw 2004). Such controlled modeling experiments inherently involve a bounded subset of real-world phenomena in order to identify important relationships and causal processes, rather than to reconstruct the world (past or present) *in silico*. Importantly, such models are constructed from the bottom up, requiring the integration of knowledge about human social processes and theory about the relationships among individual actors and groups at multiple scales to create the algorithms which drive agent perception, decision-making, and action. In a sense, model building in this way is theory building, and especially suited to the application of CAS concepts about human systems (Miller and Page 2007). Used in this way, building computational models can help refine our concepts about the operation of societies, and the models can serve as complex hypotheses that can be tested against the empirical record of archaeology. Below, I present an example of some ways in which a simple computational model can be used to study complex behaviors of human socio-ecological systems.

Modeling Complexity in Small-Scale SES

One of the first computational models I developed, simulated some of the socio-ecological dynamics of small-scale, subsistence farming. I initially built the model to answer a question about the relationship between the observable archaeological record and the dynamics of past land-use and landscape change for small-scale early Puebloan societies of the upland American Southwest (Barton 2013; Peeples *et al.* 2006). In the course of systematic, patch-based survey in the middle reaches of Chevelon Creek (Apache-Sitgreaves National Forests, Arizona), I observed that small farming sites were spaced at regular intervals. These sites seemed to have been occupied for relatively short periods of time by small numbers of people, on the basis of site size, limited midden accumulations, and lack of apparent architectural elaboration. A preliminary analysis of ceramics also indicated that the sites may not have been inhabited simultaneously. I suggested that farming households using swidden cultivation, exhausted the productive potential of the thin soils of the Colorado Plateau along Chevelon Creek after only a few years of use, and that these soils regained fertility so slowly that they were permanently exhausted as far as the Puebloan farmers were concerned. Households then moved to a new farmstead, burned the pinyon/juniper woodland to clear and fertilize fields and started the cycle again. Over the long-term, this practice created regularly spaced archaeological sites as households repeatedly moved to locales that had not previously been farmed.

While this narrative sounded reasonable, it glossed over the complex interactions of multiple households making independent decisions about where to farm, conditional not only on idiosyncrasies of individual decision-making and biophysical conditions, but also on past and present action of other farming households. In reality, it was not possible to account for these complex dynamics in detail within narrative prose. Moreover, although I could show the spatial patterning, there was no way to confirm that the observed site distribution could have been formed in this way using standard archaeological inferential methods. So I created a simple farming model to test whether or not it was possible that swidden farming practices by a few initial households in an environment of rapidly exhausted soils could produce an evenly distributed pattern of sites. I use a revised and more sophisticated version of that model here to illustrate the potential of computational modeling for the study of human societies and long-term socio-ecological change as CAS.

The model, *swidden farming v.2*[1], is constructed in Netlogo (v. 5.03; Wilensky 1999), a powerful but easy to use platform for constructing, running, and visualizing ABMs. Netlogo also includes the "Behavior Space" environment for setting up and

[1] *swidden farming v.2* can be downloaded from the Computational Modeling Library of CoMSES Net (the Network for Computational Modeling in the Social and Ecological Sciences): http://www.openabm.org/model/3826.

running models as experiments in which parameters are systematically varied and output saved to *csv* files that can be read by spreadsheet, statistics, or database applications. The *swidden farming v.2* model is abstract in that it does not use real-world landscapes or values for farming labor and harvest returns. However, it captures many of the key dynamics of small-scale farming and is useful for studying the impact of land-use on settlement and other CAS dynamics.

The model can be run in *controlled* and *adaptive* modes. In the controlled mode, the researcher controls all the parameters that govern land-use, and sets them prior to running the model. These land-use parameters include: 1) the initial number of households that start a simulation, 2) the minimum amount of accumulated resources for a household to fission and form a new household, 3) the maximum distance farmers travel to cultivate fields, and 3) the level of low resource returns at which a household will decide to abandon a farm and move to a new locale. All households begin with an arbitrary 100 *energy units*. These energy units serve as the *currency* for land use costs, returns, and decisions (in human behavioral ecology models, calories often serve the currency for costs and returns (Winterhalder and Smith 2000)). For example, the resource levels at which a household will fission and reproduce itself is expressed as a percentage of the initial 100 energy units. The researcher also controls a number of environmental parameters, including: (a) harvest return, (b) costs to clear land, and (c) costs to farm—all expressed as percentages of the initial energy units—along with (d) the rate at which fertility is lost when a parcel of land is farmed, and (e) is regained by soil when a patch is left fallow (in energy percentage lost/gained per time unit). A percentage of *bad years* can be set during which harvests are only half the normal. Finally, there are settings for land ownership and an adaptive mode that will be discussed below.

The landscape of the virtual world that farming households inhabit is initially covered completely by woodland. Households select land parcels (*patches* in Netlogo terminology) that they clear of vegetation to farm. Each modeling cycle, each household selects a parcel to cultivate within the radius of the maximum distance it will travel to farm. Land is selected so as to maximize farming returns and minimize the labor costs of land clearance and walking from farmstead to field. Land farmed in a previous cycle needs less labor for clearing, but will produce lower returns because fertility declines the more it is cultivated. If a parcel is left fallow, it begins to regrow vegetation and can return to woodland after 50 modeling cycles. Fallowed land may also regain fertility if the researcher has set a non-zero rate for soil rejuvenation.

Social Dynamics and the Archaeological Record

Figure 1 shows the *swidden farming v.2* ABM interface at an early stage of a simulation run, when small farms are just beginning to spread across the virtual world. The model was instantiated with the settings shown in Fig. 1 and a single farming household placed at a random location in the virtual world, and the simulation repeated five times. During each simulation, households farm, exhaust the surrounding soils, and move to new localities. If households accumulate enough energy (50 % more than their initial energy for this particular set of parameters) to reproduce themselves by fissioning, the daughter household then moves to a new locale nearby to establish a new farmstead. Over time, soil fertility drops, harvest

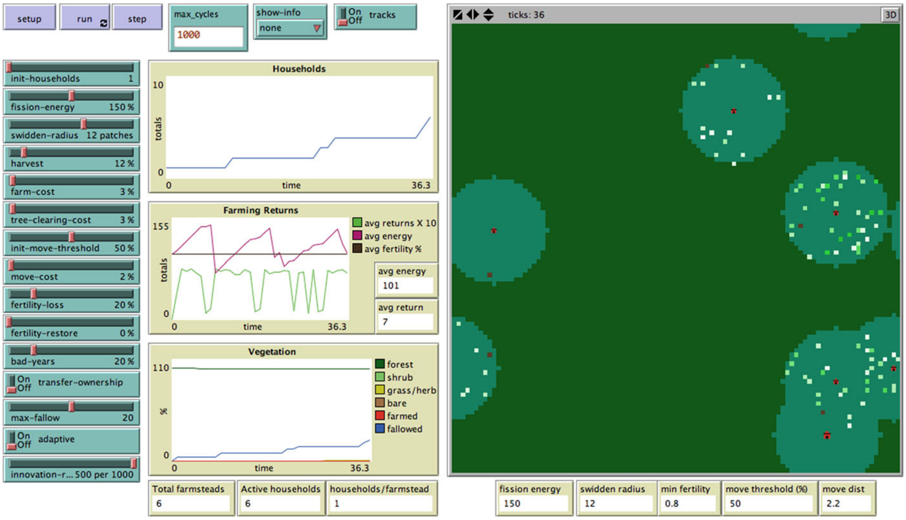

Fig. 1 Netlogo interface of the swidden farming v.2 ABM. In the main display window (*right*), the *dark green background* is uncleared woodland that has not been claimed by a household. *Lighter green circles* are areas of uncleared woodland that have been claimed by a household. Farmsteads are indicated by *red* house icons in the center of the *lighter green circles*. *Brown patches* are currently farmed; *white through light green patches* are fallowed parcels that are regrowing vegetation. Controls for setting model parameters are on the *left*. *Graphs* and *small monitor windows* indicate current state of model variables

returns decline, and the amount of energy that each household can accumulate likewise declines (Fig. 2). As a result, the population declines (Fig. 3) and farms are abandoned to become archaeological sites as households die, disperse, or move elsewhere. Eventually, the population drops to zero and the region is abandoned, ending the simulation and leaving an apparently even distribution of sites (Fig. 4). Because there is considerable stochasticity in exactly which plot of land a household farms at any given time and in where the household will move if it abandons a farm, no two runs of the simulation are identical. This is the common situation with ABM,

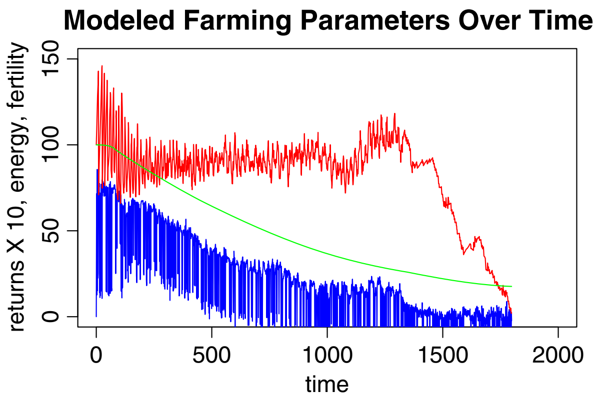

Fig. 2 Farming results over time for model with settings shown in Fig. 1 and no regain of fertility (see text). *Red line* (top) is mean energy per household, *green line* (center) is mean fertility per land parcel, and *blue line* (bottom) is mean net farming returns (in energy units) per cultivated parcel of land. Time is in model cycles ("ticks" in Netlogo terminology)

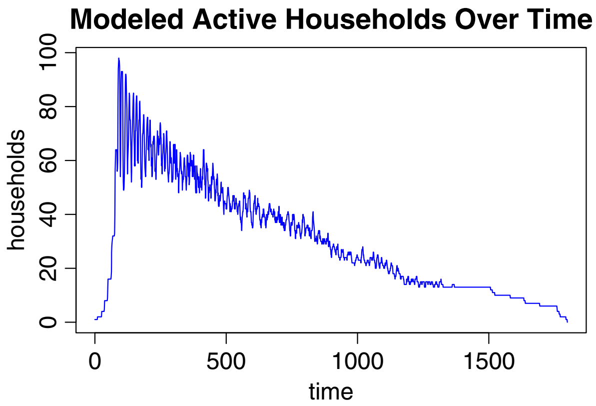

Fig. 3 Number of active households over time for model shown in Figs. 1 and 2 (see text)

making it important to carry out multiple repetitions of a simulation. This example simulation was repeated five times, with very similar results. Figure 5 shows the results of a nearest neighbor analysis that confirms the visual assessment of evenly distributed archaeological sites produced by the model.

The ABM shown here does not demonstrate conclusively that a combination of shifting cultivation and soil exhaustion actually did create the observed pattern of sites in the real-world archaeological record along middle Chevelon Creek. But it does show that such social-natural interactions would produce such a record. Other evidence will be necessary to test whether this is a better explanation than alternatives (e.g., a mass migration of farmers simultaneously occupied the region, dividing the land among themselves).

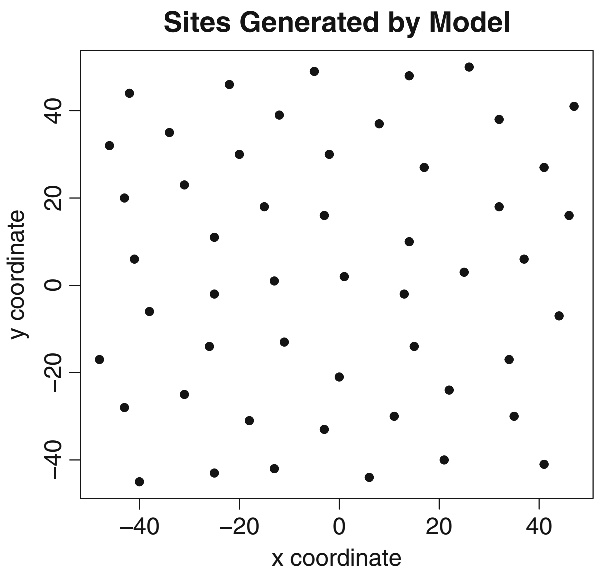

Fig. 4 Spatial distribution of archaeological sites (abandoned farmsteads) at the end of the simulations shown in Figs. 1, 2, and 3 (see text)

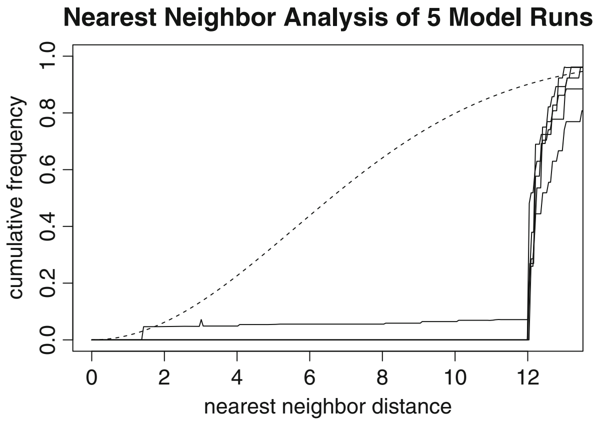

Fig. 5 Nearest neighbor analysis of archaeological site distributions created by five repeated simulations of the model shown in Figs. 1, 2, 3, and 4. *Solid lines* show cumulative distribution functions (CDF) for distances between each site and its nearest neighbor. *Dashed line* shows the CDF for a random (Poisson) distribution of the same number of sites. The fact that all sites CDFs are far below the random CDF for nearest neighbor distances indicates that they are very evenly distributed

Thresholds, Phase Change, and Emergence

In such computational modeling experiments, there can be clear and unsurprising relationships between systematic changes in parameters and simulation outcomes. For example, allowing the soil to rejuvenate in the *swidden farming v.2* ABM at even a modest 2 % fertility gain per cycle allows the population of household agents to reach a demographic equilibrium where the creation of new households is balanced by the death or dispersal of other households (Fig. 6). Similarly, increasing harvest returns allows more households to establish farms, creating a denser population.

However, not all changes lead to such easily predictable results. As noted above, one property of CAS is that causation can be non-linear, with some large changes in

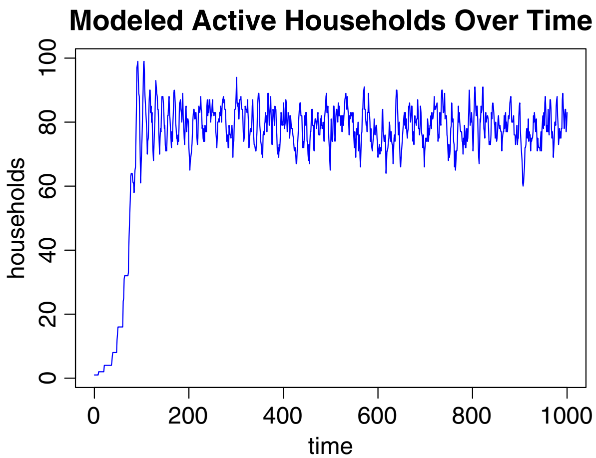

Fig. 6 Number of active households over 1,000 simulation cycles for a model with settings identical to those shown in Figs. 1, 2, 3, 4, 5, and 6 but with soil fertility regained at a 2 % per model cycle rate if a land parcel is not cultivated

system components having minimal impacts at the system level, while other small changes can significantly alter the system in unexpected ways. Also, an accumulation of small changes in agent behavior may have little impact on the system as a whole up to a point, but if they pass a *threshold* or *tipping point*, the system can rapidly reconfigure into a new state—sometimes referred to as a *phase change*. Often, when archaeologists are faced with explaining significant, rapid change in social systems, there is a tendency to attribute large changes to large, external causes—significant climate change, invasion by another society, epidemics. But from a CAS perspective, we do not necessarily have to look for large scale causal phenomena to explain social phase changes like explosive growth or collapse; these can result from an accumulation of bottom-up small changes that pass a tipping point. However, the inherent non-linear causality of CAS makes it difficult to trace the dynamics of system change in such cases. Experimental computational modeling can help explore the dynamics of emergence and narrow the range of plausible explanatory hypotheses to be tested.

The *swidden farming v.2* ABM provides an example of how computational modeling can help to identify small-scale changes that result in system-level emergent behaviors. In the preceding example, a household claimed exclusive use of its surrounding territory for farming until it died or abandoned the farmstead and moved to a new locale. This is not an unreasonable way to model small-scale farming. However, it is also possible that if a household does not need to use all of its territory to provide sufficient resources for survival and growth, it could transfer some of its unused land to another household. This ability to transfer land ownership to another individual or group is common in market economies like the United States, and also in small-scale societies with variation in the amount of time land must lie idle before the original owner loses control (Park 1997). The "transfer-ownership" option in the model interface (Fig. 1) makes land parcels initially claimed by one household available to other households if they have not been used a length of time set with the "max-fallow" slider. The model makes no assumption about the nature of a transfer of ownership transaction, but only that it is possible for unused land originally claimed by one household to be available for use by another household. The surprising results are shown in Fig. 7.

The amount of time that a parcel of land must remain idle prior to being available for transfer was set to 20, 10, 5, and 3 cycles, and the simulation repeated five times for each setting. Because households do not die out or abandon the area, each simulation ran for a standard 1,000 modeling cycles. When the amount of time that a parcel must be idle before it can be transferred is long (max-fallow=20 cycles), the main result is that many more people can occupy the landscape. Outside of the transfer of ownership possibility, the model settings in Fig. 7 are identical to those in Fig. 6. Yet, the maximum number of households simultaneously active is 10–20 times larger than without the transfer of ownership option. If the amount of time a parcel must remain fallow before being transferred declines to 10 cycles, population dynamics show no apparent difference from the 20-cycle limit.

However, when the fallow time before ownership transfer drops to five cycles, the behavior of the system changes radically. There is a very rapid rise in the number of households, followed by an equally rapid drop. The population subsequently can remain relatively stable or oscillate between rapid growth and decline subsequently (the value of multiple repetitions of a computational model run are apparent here). When the fallow time before transfer drops to three cycles, the system exhibits a

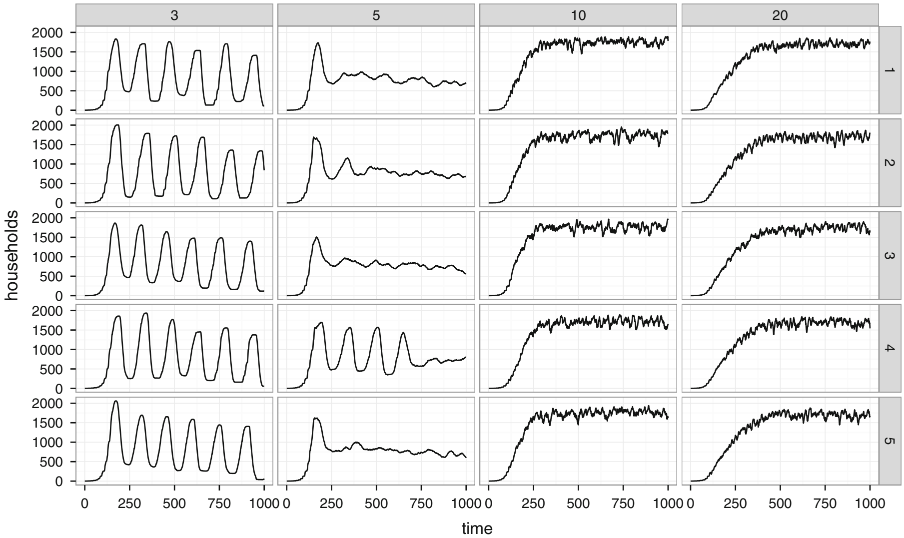

Fig. 7 Number of active households over 1,000 simulation cycles for a model with settings identical to Fig. 6 (i.e., with a 2 % soil rejuvenation rate), but with the transfer of ownership option enabled (see text). Each column shows population over time for land tenure rules that require a parcel to be fallow or idle for 20, 10, 5, and 3 cycles before it is available for transfer to another household. Each row shows a repetition of the simulation with the column settings

boom/bust population dynamic for the entire 1,000 cyles of the simulation. This is very different from the system's behavior with no option to transfer land ownership or the requirement of a long time of disuse before transfer is allowed. A simple change in ownership rules dramatically changes the behavior of the system as a whole in a way that is very difficult to predict agent behavior but which can be identified through modeling experiments.

There is no evidence that this kind of boom/bust dynamic occurred prehistorically along the middle reaches of Chevelon Creek. Sites are small, evenly dispersed, and somewhat widely spaced. There are no large accumulations of material culture. However, such temporal patterning does occur in other contexts. In another part of the US Southwest, detailed analysis of the archaeological record documents two intervals of rapid population growth and even more rapid decline during the time span represented by the occupation of the middle Chevelon Creek region (Kohler and Varian 2010). Using sophisticated computational modeling, Kohler and colleagues attribute the demographic changes to improvements in farming practices that increased carrying capacity and warfare associated with the social and ecological stresses of higher population density. It would be interesting to test the impacts of land tenure changes shown here in their modeling environment. That fact that such a test can be reasonably proposed and potentially implemented, is one of the benefits of this kind of research protocol.

Adaptation

An important characteristic of societies as CAS is their ability to adapt environmental change. Adaptation is widely attributed to societies, although use of the term and perspectives on the mechanisms that underlie adaptation vary considerably (O'Brien and Holland

1992). In fact, the process of adapting is largely invisible archaeologically; it is only the preserved materials residues of resultant adaptations that can be observed in the archaeological record. From a CAS perspective, adaptation is an emergent consequence of the choices of many interacting actors. But this does not make it any more visible in the archaeological record. In a computational modeling environment, however, agents can be allowed to change their decision-making rules—to innovate—without input from the researcher controlling the experiment. When this happens in a model like the *swidden farming v.2* ABM, where household agents can reproduce, households whose decision rules allow them accumulate sufficient energy to fission more often and die/disperse less often can become more numerous than other households. This is an example of a *genetic algorithm* implemented in an ABM context (Holland 1992; Mitchell 1998). When the "adaptation" option is enabled for the *swidden farming v.2* ABM, households ignore most of the researcher settings for decision rules, including (a) rules for the amount of accumulated resources at which a household will fission, (b) the maximum distance farmers will travel to fields, (c) the energy level at which a household will decide to abandon a farm and move to a new locale, and (d) the maximum distance a household will move to establish a new farmstead. For the starting households of the simulation, these decision rules are set randomly, representing variability in social practice among households. If a household fissions, the daughter household usually will keep the same rule set as the parent. However, there is a chance—controlled by an "innovation rate" that is set at the beginning of the simulation—that the daughter household will innovate and choose a new value for one of these decision rules. The drivers of innovation are of considerable interest, of course (Acemoglu *et al*. 2009; Boyd and Richerson 1985; Holland 1996; Martin and Simmie 2008; Shennan 2001). But to provide a simple example here, innovations are chosen stochastically within a reasonable range of values.

The *swidden farming v.2* ABM was instantiated with 50 agents to maximize initial agent variability, and the innovation rate was set to a relatively high value of 100/1,000 cycles per agent. A set of experiments were performed in which the model was run in adaptive mode for five repetitions of 1,000 cycles. The transfer of ownership option was enabled, with only three cycles of non-use before a land parcel was available for transfer, so that successful agent innovations would adapt the system to a stressful environment of population boom and bust. Characteristics of all household agents surviving after 1,000 cycles were analyzed for all five repetitions. To facilitate this analysis, a hierarchical cluster analysis was carried using the decision variables set by the agents, resulting in two distinct clusters.

The values for the farming decisions for the two household clusters are shown in Fig. 8. Most households fit into the cluster group 1 pattern. These households are more mobile, abandoning farmsteads when their energy drops only a little below its initial value. They cultivate fields up to 12–13 patches away from their farmsteads, and tend to move three times the maximum distance farmed to establish a new farmstead. Group 1 is divided into two subgroups with regards to fissioning: most households reproduce themselves when they accumulate energy of only 30 % or their initial amount; others will not fission until they accumulate more than their initial energy level.

Group 2 households are much less numerous and employ a very different land-use strategy. They are more sedentary do not move until their energy drops to below 75 % of the initial value—and many will not move until it drops below 30 % of the initial value. Like group 1 households, they tend to establish new farmsteads about three

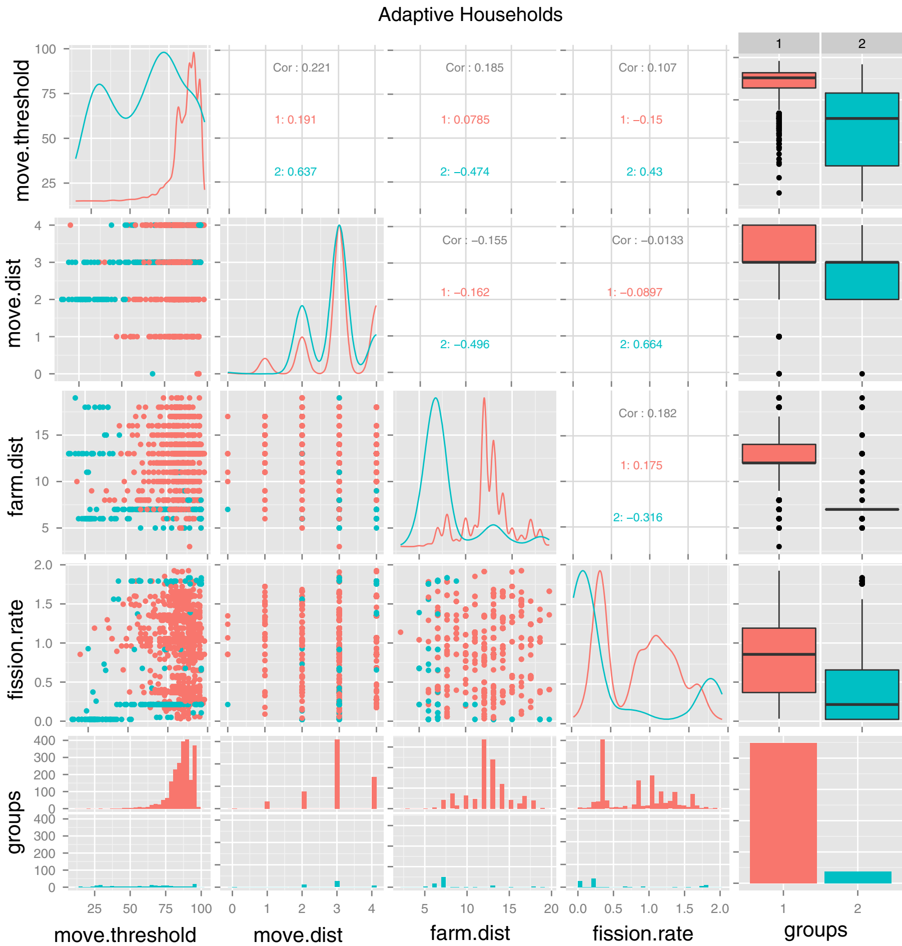

Fig. 8 Summary of results of modeling with adaptive agents showing decision strategies for the agents that survived after 5 repetitions of a 1,000-cycle simulation (see text). These strategies are characterized by a set of decision variables, including: energy level that triggers a household to move to a new locale (*move.threshold*), the distance a household will move from its prior location to establish a new farmstead due to either poor returns or after fissioning (*move.dist*), the maximum distance from a farmstead that a household will cultivate land (*farm.dist*), and the minimum energy level at which a household will fission and reproduce itself (*fission.rate*). The color-coded (red and blue) *group* variable indicates 2 different land-use strategies identified by cluster analysis (see text). The density plots (*line graphs*) along the diagonal compare frequency distributions of each variable reported for each of the two groups. *Below the diagonal* is a scatterplot matrix showing covariance between different decision variables; *Above the diagonal*, text indicates the correlation coefficients for the corresponding scatterplot in the lower left—for all agents combined (in *gray*) and for the agents in each *group* (color-coded in *red* and *blue*). Along the *right* and *bottom margins* are graphs (*box plots* and *bar graphs*) showing the distributions of each of the decision variables by *group*

times their maximum farming distance from their old residence, but this farming distance is much shorter than for group 1 households—only 6–7 patches. Finally, group 2 households will reproduce when they have only accumulated about 25 % of their initial energy. From this short and simple experiment, it is clear that at least two different kinds of household-level strategies can permit agents to be successful in the kind of socio-natural environment that creates boom-bust population oscillations.

There is another way in which CAS/model adaptation can benefit archaeological research. Archaeologists often want to know the kinds of actor-level practices that generate the system-level material remains of the archaeological record. Systematic adaption-mode computational modeling can help narrow the possibilities to a manageable set of agent behavioral combinations to generate more readily testable hypotheses. Environments like the *Behavior Search* extension for NetLogo (http://www.behaviorsearch.org) can use genetic algorithms to create an environment in which models instantiated with different parameters become meta-agents adapting to an "environment" specified by a desired model result (e.g., a pattern found in the empirical archaeological record). Model parameters can be varied stochastically or according to a desired innovation function; models that come closer to matching the desired pattern are more likely to "reproduce" and create new models. The result is a population of models that converge on the desired solution. The parameters (e.g., agent decision rules) of the most successful models represent a range of values or characteristics more likely than others to create the observed empirical pattern.

As noted above for the Chevelon region, one of the fundamental issues of inference-based archaeological reconstructions of past societies is that the same empirical patterns can be produced by quite different socio-ecological processes. Generating knowledge of the human past only from such inductive interpretations of an inherently incomplete archaeological record can lead to insoluble arguments (Barton 2013). Using genetic algorithms to automatically search through a large universe of possible human decisions and interactions, to identify those combinations whose emergent results best match the empirical record offers archaeology a suite of powerful conceptual and methodological tools to advance our understanding of long-term social change.

Concluding Thoughts

It is important to be clear that there is no inherent relationship between CAS and social complexity as normally discussed by archaeologists. Rather, a CAS approach can be useful for understanding the behavior and evolution of human societies exhibiting a diversity of organizational forms, including but not limited to those social configurations commonly considered complex. Nevertheless, because CAS concepts can scale up across all human societies, they provide a conceptually coherent set of processes and structures that can used to track the rise of social complexity (Adams 2001; Bernabeu Auban *et al*. 2012; Feinman 2013). This makes them a particularly valuable tool set for both tracking and explaining social change.

The isomorphic processes and common vocabulary of CAS concepts are not limited to human social organization, but are being applied much more broadly across dynamic systems (Barabasi 2012). This opens the door to diverse comparative studies, where simpler phenomena that can be studied under controlled conditions can serve as model systems to help better understand human social dynamics, and where the rich knowledge of human society can inform our understanding of CAS more broadly (Aktipis 2006; Fewell *et al*. 2009; Peter and Davidson 2009).

Finally, as a historical and largely observational field, it has been difficult for archaeology to take full advantage of many of the most useful scientific protocols that lead to the construction and application of a robust and coherent body of theory to explain the long-term dynamics of human sociality and the interactions between societies and the biophysical world. These protocols that center on the cycle of inductive hypotheses generation and deductive hypotheses testing are most strongly associated with scientific fields having a strong laboratory component, where controlled experiments make the inductive/deductive cycles easier to carry out and evaluate. This is not to say that fields like archaeology cannot support deductive as well as inductive protocols, but that deductive hypothesis testing seems more difficult to implement. Certainly, for all the talk of classical scientific methods in archaeology for over half a century, most archaeological practice is strongly inductive, generating inferences about the past from the archaeological record. However, in spite of ongoing improvements in data collection methods and slow, but inexorable spread of quantitative methods, the archaeological record usually is simply too sparse, fragmentary, and jumbled to make reliable inferences about all but the most trivial of past events (Barton *et al*. 2012; Barton and Riel-Salvatore 2012; Shennan 2002).

On the other hand, the archaeological record offers a rich and varied source of empirical information for testing and refining formal models, encompassing enormous diversity in human sociality at a global scale. The challenge lies in designing models so that they can be tested against this record. When used in this way, the incomplete and altered nature of the record is less problematic than when it is used to "reconstruct" the dynamic, complex systems that comprise human societies.

The combination of CAS concepts and computational modeling provide a powerful set of conceptual and methodological tools that can give archaeology—and other social sciences—a laboratory component and the beginnings of a theoretical framework to complement traditional inferential explanations with more robust hypothesis testing (Kohler and van der Leeuw 2007; van der Leeuw 2004). Besides providing better understanding of past human societies, this also can make archaeological knowledge more broadly relevant and valuable for addressing general issues that pertain to socio-ecological dynamics (Barton *et al*. 2010; van der Leeuw and Redman 2002).

References

Acemoglu, D., Aghion, P., Bursztyn, L., Hemous, D. (2009). The Environment and Directed Technical Change. National Bureau of Economic Research.

Adams, R. M. (2001). Complexity in Archaic States. *Journal of Anthropological Archaeology, 20*, 345–360. doi:10.1006/jaar.2000.0377.

Aktipis, C. A. (2006). Recognition Memory and the Evolution of Cooperation: How Simple Strategies Succeed in an Agent-Based World. *Adaptive Behavior, 14*, 239–247. doi:10.1177/105971230601400301.

Altaweel, M.R., Wu, Y. (2010). Route Selection and Pedestrian Traffic: Applying an Integrated Modeling Approach to Understanding Movement. *Structure and Dynamics,* 4.

Bankes, S. C., Lempert, R., & Popper, S. (2002). Making Computational Social Science Effective: Epistemology, Methodology, and Technology. *Social Science Computer Review, 20*, 377–388.

Barabasi, A.-L. (2012). The network takeover. *Nature Physics, 8*, 14–16. doi:10.1038/nphys2188.

Barton, C. M. (2013). Stories of the past or science of the future? archaeology and computational social science. In A. Bevan & M. W. Lake (Eds.), *Computational Approaches to Archaeological Spaces* (pp. 151–178). Walnut Creek: Left Coast Press. in press.

Barton, C. M., & Riel-Salvatore, J. (2012). Agents of change: modeling biocultural evolution in Upper Pleistocene western Eurasia. *Advances in Complex Systems, 15*, 1150003–1–1150003–24. doi:10.1142/S0219525911003359.

Barton, C. M., Ullah, I. I. T., & Mitasova, H. (2010). Computational modeling and Neolithic socioecological dynamics: a case study from southwest Asia. *American Antiquity, 75*, 364–386.

Barton, C. M., Ullah, I. I. T., Bergin, S. M., *et al*. (2012). Looking for the future in the past: long-term change in socioecological systems. *Ecological Modelling, 241*, 42–53. doi:10.1016/j.ecolmodel.2012.02.010.
Bentley, R. A., & Maschner, H. D. G. (2003). *Complex Systems and Archaeology: Empirical and Theoretical Applications*. Salt Lake City: University of Utah Press.
Bernabeu Auban, J., Moreno Martín, A., & Barton, C. M. (2012). Complex systems, social networks and the evolution of social complexity. In M. Berrocal, L. García Sanjuán, & A. Gilman (Eds.), *The Prehistory of Iberia: Debating Early Social Stratification and the State* (pp. 23–37). New York: Routledge.
Boyd, R., & Richerson, P. J. (1985). *Culture and the evolutionary process*. Chicago: The University of Chicago Press.
Carballo, D.M, Roscoe, P., Feinman, G.M. (2013). Cooperation and Collective Action in the Cultural Evolution of Complex Societies. *Journal of Archaeological Method and Theory*. in press, online: 1–36. doi: 10.1007/s10816-012-9147-2.
Chase, A. F., Chase, D. Z., Fisher, C. T., *et al*. (2012). Geospatial revolution and remote sensing LiDAR in Mesoamerican archaeology. *Proceedings of the National Academy of Sciences, 109*, 12916–12921. doi:10.1073/pnas.1205198109.
Cowan, G. A., Pines, D., & Meltzer, D. (1994). *Complexity: metaphors, models, and reality*. Reading, MA: Addison-Wesley.
Cowgill, G. L. (2004). Origins and Development of Urbanism: Archaeological Perspectives. *Annual Review of Anthropology, 33*, 525–549.
Feinman, G. M. (1998). Scale and social organization: Perspectives on the archaic state. In G. M. Feinman & J. Marcus (Eds.), *Archaic states* (pp. 95–133). Santa Fe, NM: School of American Research Press.
Feinman, G. M. (2011). Size, Complexity, and Organizational Variation: A Comparative Approach. *Cross-Cultural Research, 45*, 37–58. doi:10.1177/1069397110383658.
Feinman, G. M. (2013). The Emergence of Social Complexity: Why More than Population Size Matters. In D. M. Carballo (Ed.), *Cooperation & Collective Action: Archaeological Perspectives* (pp. 35–56). Boulder: University Press of Colorado.
Fewell, J. H., Schmidt, S., & Taylor, T. (2009). Division of labor in the context of complexity. In J. Gadau & J. H. Fewell (Eds.), *Organization of Insect Societies: From Genome to Sociocomplexity* (pp. 584–610). Cambridge: Harvard University Press.
Flannery, K. (1986). *Guilá Naquitz: Archaic Foraging & Early Agriculture in Oaxaca*. New York: Academic Press.
Gaines, S. W., & Gaines, W. M. (1997). Simulating Success or Failure: Another Look at Small-Population Dynamics. *American Antiquity, 62*, 683–697.
Hegmon, M. (1989). Risk Reduction and Variation in Agricultural Economics: A Computer Simulation of Hopi Agriculture. *Research in Economic Anthropology, 11*, 89–121.
Henrickson, L., & McKelvey, B. (2002). Foundations of "new" social science: Institutional legitimacy from philosophy, complexity science, postmodernism, and agent-based modeling. *Proceedings of the National Academy of Sciences, 99*, 7288–7295.
Holland, J. D. (1992). Genetic algorithms. *Scientific American, 267*, 44–50.
Holland, J. H. (1996). Hidden order: How adaptation builds complexity. Basic Books.
Holland, J. D. (2000). *Emergence: From Chaos to Order*. Oxford: Oxford University Press.
Hooper, P. L., Kaplan, H. S., & Boone, J. L. (2010). A theory of leadership in human cooperative groups. *Journal of Theoretical Biology, 265*, 633–646. doi:10.1016/j.jtbi.2010.05.034.
Johnson, G. (1982). Organizational structure and scalar stress. Theory and Explanation in Archaeology.
Kohler, T. A., van der Leeuw, S. E. (2007). The model-based archaeology of socionatural systems. School for Advanced Research Press.
Kohler, T. A., & Varian, M. D. (2010). A Scale Model of Seven Hundred Years of Farming Settlements in Southwestern Colorado. In M. S. Bandy & J. R. Fox (Eds.), *Becoming Villagers: Comparing Early Village Societies* (pp. 37–61). Tucson: University of Arizona Press.
Kvamme, K. (2007). Integrating Multiple Geophysical Datasets. *Remote Sensing in Archaeology*, pp 345–374.
Lansing, J.S. (2003). Complex Adaptive Systems. *Annual Review of Anthropology*, 32.
Martin, R., & Simmie, J. (2008). Path dependence and local innovation systems in city-regions. *Innovation: Management, Policy & Practice, 10*, 183–196.
Miller, J. H., & Page, S. E. (2007). *Complex adaptive systems: an introduction to computational models of social life*. Princeton, N.J.: Princeton University Press.
Mitchell, M. (1998). *An introduction to genetic algorithms, 1st MIT Press pbk*. Cambridge, Mass: MIT Press.
Mitchell, M. (2006). Complex systems: Network thinking. *Artificial Intelligence, 170*, 1194–1212. doi:10.1016/j.artint.2006.10.002.
Mitchell, M. (2009). *Complexity: A guided tour*. USA: Oxford University Press.

Moran, E. F. (1991). The ecosystem approach in anthropology: from concept to practice. University of Michigan Press.
O'Brien, M. J., & Holland, T. D. (1992). The role of adaptation in archaeological explanation. *American Antiquity, 57*, 36–59.
Park, T. K. (1997). Indirass and the political ecology of flood recession agriculture. In A. E. Nyerges (Ed.), *The Ecology of Practice: Studies of Food Crop Production in Sub-Saharan West Africa* (pp. 77–95). Amsterdam: Gorden and Breach.
Peeples, M., Barton, C M., Schmich, S. (2006). Resilience lost: intersecting landuse and landscape dynamics in the upland southwest. *Ecology and Society*, 12.
Peter, I. S., & Davidson, E. H. (2009). Modularity and design principles in the sea urchin embryo gene regulatory network. *FEBS Letters, 583*, 3948–3958. doi:10.1016/j.febslet.2009.11.060.
Rappaport, R. A. (1971). Pigs for the ancestors: Ritual in the ecology of a New Guinea people. Yale University Press.
Shennan, S. (2001). Demography and Cultural Innovation: A Model and Its Implications for the Emergence of Modern Human Culture. *Cambridge Archaeological Journal, 11*, 5–16. doi:10.1017/S0959774301000014.
Shennan, S. (2002). *Genes, Memes, and Human History: Darwinian Archaeology and Human Evolution*. London: Thames and Hudson.
Simon, H. A. (1962). The architecture of complexity. *Proceedings of the American Philosophical Society, 106*, 467–482.
Smith, M. E. (2009). V. Gordon Childe and the urban revolution: an historical perspective on a revolution in urban studies. *Town Planning Review, 80*, 2–29.
Strogatz, S. H. (2001). Exploring complex networks. *Nature, 410*, 268–276. doi:10.1038/35065725.
Turchin, P. (2003). *Historical dynamics: why states rise and fall*. Princeton: Princeton University Press.
Van der Leeuw, S. E. (2004). Why model? *Cybernetics and Systems: An International Journal, 35*, 117–128. doi:10.1080/01969720490426803.
Van der Leeuw, S. E., & Redman, C. L. (2002). Placing archaeology at the center of socio-natural studies. *American Antiquity, 67*, 597–605.
Wandsnider, L. (1992). The spatial dimension of time. In J. Rossignol & L. Wandsnider (Eds.), *Space, Time, and Archaeological Landscapes* (pp. 257–282). New York: Plenum.
Wilensky, U. (1999). NetLogo. Center for Connected Learning and Computer-Based Modeling. Northwestern University.
Winterhalder, B., & Smith, E. A. (2000). Analyzing adaptive strategies: human behavioral ecology at twenty-five. *Evolutionary Anthropology, 9*, 51–72.
Wobst, H. M. (1974). Boundary conditions for paleolithic social systems: a simulation approach. *American Antiquity, 39*, 147–178.