Exploratory Agent-based Models: Towards an Experimental Ethnoarchaeology

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Abstract

Understanding what is meant by terms like parameter space, attractor, and basin of attraction is prerequisite to an appreciation of how agent-based models can be used to conduct experimental ethnoarchaeology. An argument that agent-based models should be used principally as exploratory tools is couched within a brief review of some techniques used to investigate the nonlinear dynamics of complex systems. To illustrate the archaeological utility of a modeling framework patterned after that which has been used to study such complex systems, I present some of the results of a simple agent-based model that investigates the evolution of Plio-Pleistocene hominin food sharing accordingly.

1 Introduction

The number of archaeologists who have applied techniques used to investigate the nonlinear dynamics of complex systems to the study of human behavior is small, but growing (see Beekman and Baden 2005; Bentley and Maschner 2003a; Kohler and Gumerman 2000; McGlade and van der Leeuw 1997). It is not altogether surprising that relatively few archaeologists have looked to the likes of mathematicians and physicists for help in their efforts to model the past, as historical scientists and physical scientists have traditionally gone about their modeling research in qualitatively different ways. One obvious difference stems from the fact that many (but not all) physical scientists can act as their own informants in ways that historical scientists cannot. That is, a physical scientist can run a series of controlled, repeatable experiments designed to explore how a wide range of initial conditions affects the phenomenon of interest in a laboratory, while an archaeologist cannot travel back in time to observe how subtle changes made to the subjects' environment affect the archaeological record. Because we lack the ability to conduct controlled, repeatable experiments on our subjects directly, we are often tempted to use models to simulate (i.e., emulate, or imitate) the ways in which we think our subjects behaved in the past. Unfortunately, the act of merely operationalizing one's preconceptions of a complex system *in silico* (i.e., through a computer application or computer simulation) does not guarantee that one will learn anything new about that system. Agent-based emulation will rarely contribute to a better understanding of unknown phenomena because it bypasses the crucial process of testing alternative assumptions against empirical data. Instead, emulation projects often reinforce one or another untestable, verbal model, which more often than not then serves as archaeological "explanation" by default rather than by scientific merit.

Archaeologists cannot settle for models that begin with untestable hypotheses and end in circular explanations. Rather than merely replicating field data *in silico*, I argue that archaeologists stand to improve their interpretations by using simple models to explore numerous possible histories and then testing with empirical data expectations generated by a deeper understanding of the dynamics they exhibit. To that end, this paper discusses how agent-based models provide tools for archaeologists to explore alternative cultural histories in a manner reminiscent of how other scientists regularly explore the parameter spaces of nonlinear dynamical systems. After reviewing the concept of alternative cultural histories in the context of Stephen J. Gould's famous "tape of history" thought experiment, I briefly discuss some of the terms that are central to modeling nonlinear dynamical systems. Next, some of the results of an agent-based model currently being used to study the evolution of altruistic food sharing in Plio-Pleistocene hominins are presented to illustrate the archaeological utility of this methodology. The paper concludes with some thoughts on how exploratory agent-based models can be used to generate archaeological inferences from the null-up, and how they can move us closer to an experimental ethnoarchaeology. The main thrust of this paper is two-fold. First, archaeological agent-based models should be used principally as tools to explore alternative cultural histories. Second, such explorations should be patterned after structured formal experiments, and those used to investigate the behavior of nonlinear dynamical systems provide a useful example.

2 Why Use Exploratory Models?

One of the main goals of archaeology is to gain a sharper understanding of how cultures change through time. History—the singular sequence of events, which includes every interaction, decision, and occurrence through time—doubtlessly played an important role in shaping the way our species looks and behaves today, but archaeological reconstructions that correctly identify each and every detail of this singular evolutionary history are unattainable. In light of this inherent limitation to the resolution of our data and the fact that we cannot experiment with human societies directly, our models of the past should utilize an exploratory experimental design—one which allows archaeologists to replay the so-called “tape of history” (Gould 1989) so that we might observe how a wide range of plausible environmental and behavioral scenarios affects artificial societies and the archaeological records they create. Because this is not the first time that an anthropologically-minded agent-based modeler has drawn attention to Gould’s analogy, it is deserving of a brief description here (see also Dean et al. 2000; Lansing 2002; Premo 2006, In press).

In discussing the importance of historical contingency to understanding evolutionary change, the late Stephen J. Gould (1989) proposed an interesting thought experiment. Imagine that Earth’s history had been captured on videotape. Now imagine replaying this tape of history, beginning from any point in the past, while observing certain “characters” (i.e., species). For the sake of the thought experiment, Gould proposes the existence of a unique tape player that can show different evolutionary outcomes, depending on both the sequence and the types of historical events that might occur during each replay of this tape of history: “the divine tape player holds a million scenarios, each perfectly sensible…the slightest early nudge contacts a different groove, and history veers into another plausible channel” (1989:320-321).

In their endeavor to retrace the trajectories of past societies, archaeologists have access to only two types of data sets. The first is a frustratingly incomplete and biased material record deposited during the one and only run of the tape of history. The second is composed of the behaviors and materials that are observable in the current “scene,” if you will, of the evolutionary tape of history—these are the details of human life as it exists today. Because we cannot realistically expect to uncover all of the details of the true tape of history given these data, archaeologists might do themselves a favor by more regularly asking questions other than: What happened in region X during period Y? Archaeologists might learn more about larger evolutionary questions by instead asking: How likely is it that behavior Q or trait Z would evolve in the population in region X during period Y given a wide range of plausible environmental conditions and alternative histories?

For example, we know from observations of contemporary societies all around the world that humans are unparalleled food sharers, but what is the likelihood that widespread altruistic food sharing would have evolved to fixation in our lineage given a different historical scenario, perhaps one that involved a slightly different climate or social structure, for example? The answer to this question lies in investigating the likelihood that qualitatively comparable evolutionary outcomes would occur in alternative social and biological environmental scenarios. We cannot rerun the real tape of history, but one of the major advantages of a computer model is that we can rerun its tape of history *in silico*, and we can even change many of its initial conditions while doing so. By observing the dynamics and material records of artificial societies as they are placed in a variety of experimental environments, one can build a better understanding of which parameters might have been important during the past as well as how small changes in those key parameters could have influenced both the trajectory of culture change and the archaeological signature it left behind.

Gould’s cosmic tape player does not imitate the past; rather, it introduces subtle historical anomalies, some of which strongly affect the subjects and/or behaviors of interest. This raises an important point about models that are built to imitate the way we think people behaved in the past: simply emulating empirically-derived archaeological patterns via computerized models does not (in fact, *cannot*) prove that those ideas about the past are correct. But by allowing one to control initial conditions while systematically playing out multiple alternatives—to replay Gould’s tape of history hundreds, or even tens of thousands, of times—agent-based models permit experimentation with numerous “what if” scenarios, many of which are likely to produce data that does not look like what we find in the field, and this is good. In fact, we often learn the most about the limits of our own assumptions when simple model results fail to match empirical patterns, or when we break our models. Thus, it is important not only to understand why a model produces data that looks like empirical data under certain conditions, but also to explain why it does not under other conditions. For the most part, archaeologists are keen on the former but neglect the latter. In short, the exploratory approach provides systematic tools for generating and testing alternative hypotheses, and for learning about why some plausible scenarios provide data that do not match our expectations. A basic understanding of how other scientists model nonlinear dynamical systems further elucidates why this distinction between emulation and exploration is important to archaeological agent-based modeling.

3 Dynamical Systems 101: Parameter Space, Attractor, and Basin of Attraction

Over the last two decades, the study of nonlinear dynamical systems has become increasingly popular as fields such as chaos theory (see Gleick 1987 for a popular account) and complexity theory (see Waldrop 1992 for a popular account) have emerged from transdisciplinary collaborations among scientists who are as dissatisfied with equilibrium-based systems theory modeling techniques as they are with the hyper-relativistic post-Modern critiques leveled at them (Bentley and Maschner 2003b). James McGlade (1995; 2003) is especially noteworthy for his sophisticated thoughts on how one might go about applying some of the techniques used to study nonlinear dynamical systems to archaeological problems. For those to whom this approach is new, a few simple definitions should provide an adequate orientation for the purposes of the following discussion (but do check out McGlade’s work when you get the chance).

A dynamical system is a theoretical construct in which an evolutionary rule (usually a mathematical algorithm) uses the current state of a deterministic system to describe the state it will display in the following time step. Although dynamical systems are commonly initialized in some kind of "random" configuration, they usually settle into a single state, or state cycle, eventually. This final state is called an *attractor*, because it is one out of many possible states from which a dynamical system cannot escape. Each attractor is surrounded by its own *basin of attraction*, which includes the region of the parameter space in which a deterministic dynamical system will inevitably "flow" to an attractor. The *parameter space* is defined by all of the values that could possibly be used to initialize the model. A common bathtub provides a useful analogy for a dynamical system. For example, think of the drain as the tub's attractor, because water cannot escape it upon entering; the porcelain reservoir as its basin of attraction, because it funnels water that has been added to the system toward the drain; and the one and only final *state* as empty, because no matter how much water is added to an unplugged bathtub, it will eventually return to the state in which it contains no water.

An interesting characteristic of *nonlinear* dynamical systems is that they often possess not just one attractor, like our simple bathtub example, but several attractors, each of which is associated with its own uniquely shaped basin of attraction. When studying the overall behavior of such systems, the most pressing question is: In which attractor will the system settle given different combinations of initial parameter values? This question can be answered by exploring the parameter space of initial conditions while recording the sizes and shapes of the various basins of attraction. This exploratory approach elucidates how a model's behavior is affected by systematic sweeps through experimental parameter values. This important information can be used to assess model sensitivity to minor changes in initial conditions.

Figure 1 provides a graphical representation of a fictional deterministic nonlinear dynamical system. The parameter space is defined by two experimental parameters (A and B), each of which can be assigned values ranging from 1 through 10. Depending on which combination of parameter values is used to initialize the model, the system may flow into one of three attractors (X, Y, or Z). The basins surrounding these attractors are indicated by irregular polygons. Note that to understand the behavior of this nonlinear system requires collecting data from a suite of experimental runs that samples the entire parameter space rather than just one small region.

Archaeologists have much to learn from this general approach to modeling complex systems. Although cultures are not truly analogous to dynamical systems (they are nonlinear, but they include stochasticity so they are decidedly *not* deterministic, and this is an important distinction), models of culture change can be studied in a similar manner because each unique combination of experimental parameter values and random number seeds provides an equally unique evolutionary scenario. When one investigates only that small region of a model's parameter space that matches preconceived expectations, many plausible evolutionary scenarios are ignored. While a more exhaustive exploration of a model's parameter space often allows one to identify the region(s) that yields artificial data that match some *a priori* expectations, it also provides information about those regions of the parameter space that do not. Thus, the simple act of exploring many possibilities can identify basins that lead to unexpected or even previously unknown attractors. Knowing not only where in the parameter space one's model matches expected values as well as where it does not, but, also, *why* this occurs, leads to a more comprehensive understanding of the unknown phenomenon of interest and, ultimately, to better explanation. This is illustrated below with the results of an exploratory agent-based model, called the Simulated Hominin Altruism Research Environment (SHARE). SHARE is programmed in Objective-C and makes use of the Swarm object libraries (www.swarm.org). SHARE's source code is freely available from the author upon request.

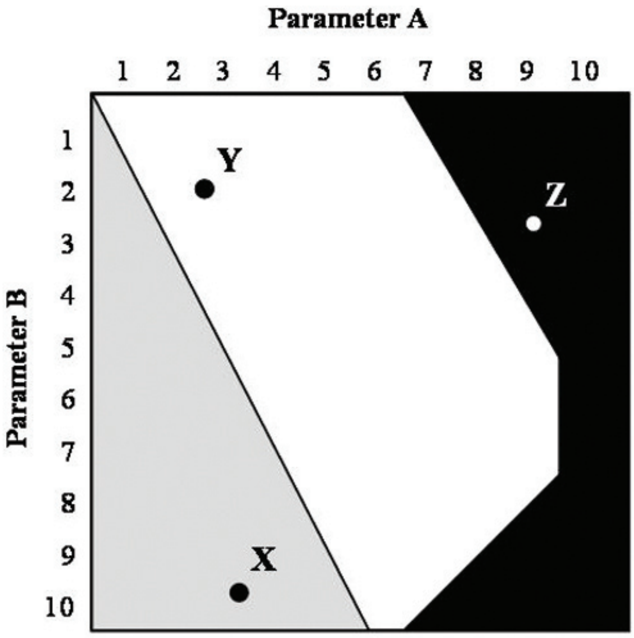

Figure 1. Within the parameter space of this fictional dynamical model are three attractors (X, Y, Z) with their respective basins of attraction (grey, white, and black polygons). When initialized with A=5 and B=3, this deterministic system will eventually settle into state Y.

4 An Exploratory Agent-based Model of the Evolution of Altruistic Food Sharing

Early studies of early hominin food sharing were heavily influenced by observations of living human groups (Isaac 1978, Lovejoy 1981), but extant and historically-documented hunter-gatherers, bound by their own historical, economic, and political contexts, represent but a small subset of possible forager societies. In contrast to these referential modeling studies, I employ an agent-based model as an exploratory behavioral laboratory to investigate how a wide range of experimental behavioral and ecological scenarios affect the evolution of altruistic food sharing traits in artificial societies of hominin agents.

To more accurately model the socio-ecological milieu of Plio-Pleistocene hominins, I 1) refocus the traditional savanna hypothesis away from open grasslands and toward fragmented patches of closed habitat, and 2) enlarge evolutionary ecological explanations of food sharing to include the selective benefits bestowed upon hierarchical levels that exist directly above that of the individual (i.e., at the level of the trait group). This approach yields a new hypothesis that the altruistic phenotypic trait of sharing food could have evolved in Plio-Pleistocene hominin populations due to the benefits it bestowed upon the fitness of subsistence-related trait groups competing with one another in an increasingly patchy ecological environment. The current research concerns itself mainly with the following question: In what range of ecological and behavioral conditions could food sharing have evolved in Plio-Pleistocene hominin populations? Thus, I use SHARE to study the relationship between ecological patchiness, altruistic food sharing, and the formation of Lower Paleolithic archaeological landscapes within the confines of an exploratory agent-based model.

Even though SHARE is a nondeterministic model, some of its results are best discussed in the parlance of nonlinear dynamical systems. Its environmental parameter space is defined by two experimental variables, Gap Size and Patch Size. Their combined values define varying levels of ecological patchiness, and by varying them I conduct what Richardson (2003) calls "weak exploration." SHARE's behavioral parameter space is defined by three qualitatively different food sharing strategies including, in order of increasing sophistication: Simple, Reciprocal, and Omniscient. A Simple prospective donor will share food if two conditions are met: 1) it possesses food in excess of its lower food share threshold, and 2) a random number is less than or equal to the value of its food sharing phenotype. Sharing by this method is based entirely upon probabilities, and, thus, it models interactions between "unintelligent" hominin agents that have neither memory of past actions nor the ability to recognize the identity of others. A Reciprocal prospective donor, on the other hand, has the ability to store and retrieve the unique individual identities of hominin agents who cooperated with or defected against it in past interactions. Reciprocal prospective donors rely upon this memory of past interactions to make food sharing decisions on an individual basis according to the following rule: share excess food with those who shared with you, but refuse those who refused you (i.e., tit-for-tat). If a prospective donor has no memory of a prospective recipient, then the initial decision about whether to share excess food follows the Simple protocol. Finally, the Omniscient strategy models the scenario in which hominin agents share information—via gossip, for example—about past social interactions so that they can correctly discern altruists from cheaters upon their very first meeting. According to Omniscient, prospective altruistic donors with excess food will share only with the prospective recipients they recognize as being altruistic, and they will choose not to share with those they identify as selfish cheaters. By running the model with each of these qualitatively different behaviors, I conduct "strong exploration" (Richardson 2003).

In SHARE, artificial societies of hominin agents have two mutually exclusive attractors: 1) the altruistic allele evolves to fixation in the population of foragers, or 2) the selfish allele evolves to fixation in the population of foragers. In other words, starting from a mixed population, which includes an equal number of altruists and egoists, each artificial society might evolve to be composed entirely of one type or the other, depending on initial conditions, the vagaries of history introduced by the stochastic model, and selection. Each of these attractors is associated with a basin of attraction (of sorts) that describes the area of the parameter space that *facilitates* one or the other state. In SHARE, these regions do not fulfill the true definition of basins of attraction because not every random number seed run in them will inevitably lead to the same attractor; stochastic events might bump the behavior of the model into an adjacent "pseudo" basin of attraction. In this respect, the analogy with deterministic dynamical systems research is not perfect. Regardless of this subtle difference, the pseudo-basins in stochastic nonlinear models provide clear indicators of the regions of the parameter space that often facilitate the evolution of altruistic food sharing as well as those that seemingly never facilitate the evolution of altruism. This coarser scale of analysis is adequate when studying trends in stochastic models rather than laws in deterministic ones.

Only after charting the behavior of the model throughout the environmental and behavioral parameter space does the effect of ecological patchiness on the evolution of food sharing become apparent. Altruistic alleles for Simple and Reciprocal food sharing strategies (Figure 2) evolve to fixation predominantly in the region of the parameter space characterized by the combination of intermediate Patch Sizes (4

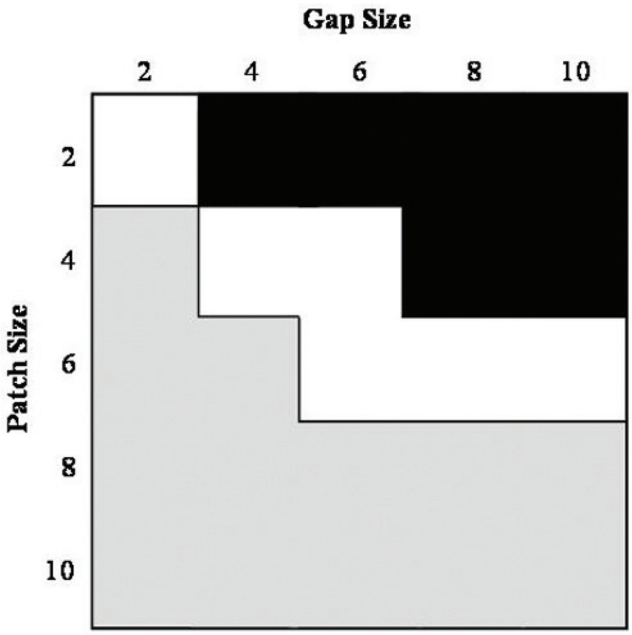

Figure 2. Analyzing the Simple and Reciprocal food sharing strategies. The white region indicates the area of the parameter space in which mixed populations of hominin foragers often evolve to pure populations of altruists—this is the basin of attraction for the evolution of simple altruistic food sharing strategies. The grey region of the parameter space leads to the evolution of pure populations of selfish foragers. The black region does not support viable populations of either allele. This figure summarizes data collected from 5,050 simulation runs.

and 6) and intermediate-to-large Gap Sizes (4, 6, 8, and 10) (see Premo 2006 for total counts). In other words, in the case of these two sharing strategies, ecological patchiness levels that support viable altruistic populations are found only along the boundary between those that are uninhabitable (the black region of the parameter space) and those in which selfish alleles are almost always successful (the grey region). This pattern clearly echoes that found by Pepper and Smuts (2000) for other altruistic traits, such as feeding restraint and alarm calling, but why? The evolution of altruism requires strong between-group selection (Sober and Wilson 1998), and the strength of between-group selection largely depends upon how genetic variation is partitioned within and among trait groups. Resource patchiness can structure the genetic variation of a population in a variety of ways, many of which weaken between-group selection. For instance, small patches result in trait groups that are too ephemeral to compete as evolutionarily meaningful groups, while large patches support large trait groups that often contain a mix of forager types. In addition, small gaps between patches do not pose deterrents for migration. Each of these conditions effectively weakens between-group selection. However, as Figure 2 illustrates, between these extremes exists a *transitional* range of resource patchiness. The experimental environments contained within this region of the parameter space provide the structure necessary to form internally homogenous and externally heterogeneous trait groups of hominin agents. In the cases of the two simpler

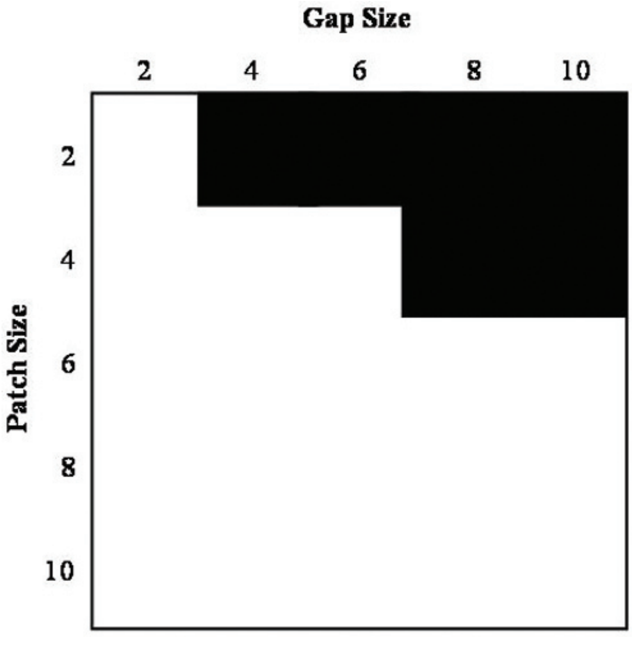

Figure 3. Analyzing the Omniscient food sharing strategy. The white region indicates the area of the parameter space in which mixed populations of hominin foragers often evolve to pure populations of altruists—this is the basin of attraction for the evolution of the more sophisticated altruistic food sharing strategy. Note that this basin has expanded significantly in comparison to that depicted in Figure 2. The black region does not support viable populations of either allele. This figure summarizes data collected from 2,525 simulation runs using only the most sophisticated food sharing strategy.

food sharing strategies (Simple and Reciprocal), it is under this rather restricted range of ecological conditions that ecological patchiness enjoys its most influential between-group selective power because of the way it non-randomly structures the interactions of an otherwise freely-mixing population of socially inept foragers (Premo 2005, 2006).

Data collected from runs that include the most sophisticated food sharing strategy (Omniscient) paint a different picture (Figure 3). Although this picture bears the signature of the same uninhabitable region, it clearly shows that greater behavioral sophistication allows the basin of attraction for altruistic food sharing to expand significantly. In this case, the altruistic allele evolves to fixation often, but by no means always, in all of the patchiness levels that are able to support viable populations, not just along the transitional diagonal. By refusing to share with individuals whom they recognize as non-cooperators, altruistic donors use their sense of prospective recipients' phenotypes to protect themselves and avoid being cheated out of valuable food. These results illustrate an inverse relationship between ecological selective power and behavioral sophistication: ecological patchiness plays only a minor role in the evolution of altruistic food sharing when more sophisticated strategies, like Omniscient, are involved.

In the final analysis, one must consider how the population genetic results of SHARE inform our understanding of how altruistic food sharing *could have evolved* in Plio-Pleistocene hominin populations. In doing so, one must keep in mind that SHARE is a null model of early hominin behavior that for now purposefully excludes traits like group-living and central place foraging to test their relevance to the evolution of altruistic food sharing. The point in using a null model is to demonstrate that these assumptions are not necessary to the evolution of even the simplest altruistic food sharing alleles under certain ecological conditions. The fact that the results of the model would probably differ had I expressly included group-living or central place foraging is something I freely admit, but it does not detract from the utility of the null model, which gives us a tool for identifying superfluous presumptions and paring our assumption-laden narrative reconstructions down to elegant explanatory models. Although there is no guarantee that this null model provides the most accurate explanation possible, this spartan version provides the best place to start the heuristic process we call modeling. During the course of this process, one might choose to address related research questions with other simple models. Alternatively, one might decide to combine a number of individually-verified models into a single, more complicated version. The potential danger of the second approach is that individually-verified models may interact in unexpected ways when combined under the umbrella of a single, overarching experimental framework: when combined, they might display combinatorial effects that are not the properties of any individual model. Although such an effect is not inevitable and there may be cases when more complicated models have something to add to our understanding of a complex problem, one should be aware of this potential problem when deciding whether or not to move from a series of simple, self-contained models to a more complex model that subsumes them. Complex models are not necessarily better than simple ones, and, in many cases, complex models will teach us much less than their simpler counterparts.

SHARE has taught us that food sharing behaviors need not be overly complicated to evolve within the transitional range of ecological patchiness. Under certain ecological conditions, even socially-sophomoric food sharing strategies could have evolved to fixation in hominin populations during the Plio-Pleistocene. The premise that early hominins displayed relatively simple food sharing strategies is more parsimonious than the traditional application of modern hunter-gatherer behaviors, and according to these results, the more parsimonious hypothesis could also be more accurate in the face of environmental fragmentation during the Pliocene in East Africa. This finding yields an interesting and conceivably testable hypothesis: if the earliest food sharing behaviors were indeed simple, a strong temporal correlation should exist between significant forest fragmentation and the spread of this altruistic behavior.

Second, we have learned that cultural sophistication liberates food sharing from a narrow, transitional range of ecological patchiness, thereby allowing altruistic alleles to evolve to fixation at higher frequencies in a larger proportion of the environmental parameter space. This finding implies that had early hominins been capable of a relatively complex version of food sharing, one which involved gossip and/or possibly even the punishment of social cheaters (not tested here), woodland fragmentation would have played a greatly diminished role in the biosocial evolutionary process. Therefore, if the earliest food sharing behaviors were culturally sophisticated, paleoanthropologists should not expect to find a strong temporal correlation between the evolution of food sharing and the fragmentation of Pliocene forests in East Africa. These are new hypotheses that can be tested against the paleoenvironmental and archaeological data collected from Lower Paleolithic localities in East Africa.

5 Generating Archaeological Interpretations from the Null-up

> The goal of understanding early hominid life in terms of itself can only be accomplished if we have strongly contrastive yet plausible alternatives. In this context, the intellectual challenge is then shifted to the methods of inference justification used by archaeologists rather than the skill with which archaeologists are capable of accommodating facts to their beliefs. (Binford 1987:21)

Exploratory models, like SHARE, provide archaeologists with the valuable opportunity to act as their own informants in building better archaeological inferences. In this case, SHARE improves our understanding of how simple cultural formation processes influence archaeological landscapes under a large variety of behavioral and ecological scenarios. It also demonstrates how agent-based models can provide powerful tools for testing the validity of archaeological inferences via experimentation with artificial societies. When employed as behavioral laboratories, agent-based models provide forums for independently generating new hypotheses. To explore alternative ways in which Lower Paleolithic landscapes *could have* formed within a behavioral laboratory, use that understanding to formulate expectations of the real world, and then test those against empirical data is to bootstrap our ideas of the past to the data we recover in the present. Contrast this approach with the subtle practice of fitting, or "tuning," models to support our ideas about the past with data we recover in the present. As Binford warns, archaeologists must not "approach the external world in search of verification for our ideas and slip into the trap of accommodating experiences to fit what we *believe* to be true" (1987:21, emphasis in original).

What I have described in this paper is a methodology for building archaeological inferences with a computational tool. Exploratory agent-based models start with theory. They allow us to build a set of expectations that can then be evaluated with observed empirical data. As a result, they can facilitate tests (of our assumptions or of a particular hypothesis) that do not suffer from the same pernicious circularity that confounds studies that use the same set of archaeological data *both* to formulate hypotheses about archaeological formation processes *and* to test them. However, not all agent-based modeling approaches are immune to circularity. Those used explicitly to imitate real world archaeological data inadvertently sacrifice independence in favor of a higher degree of "realism" (as if that can be measured). Because there are an infinite number of ways to program a computer model in order to produce artificial archaeological data that matches those we observe in the field, merely aping partially understood systems *in silico* is neither difficult nor particularly informative (see discussions of equifinality in modeling in Richardson 2003 and Premo In press). It is more informative to take a holistic approach to modeling in which one also studies why experimental data do not match those observed empirically.

The approach I have used demonstrates that question-driven, null agent-based models can be especially helpful when kept elegant. Although null models can teach us about the regions of the behavioral and ecological state space that are not addressed in overly-detailed verbal models or represented by observations of contemporary hunter-gatherers, a null model should not be the one and only stop on the route to better understanding via modeling. In the case of SHARE, I am currently in the process of comparing the population genetic and artificial archaeological results of a more complicated version of the model—one that includes group-living and zooarchaeological data—with the results obtained from the null version reported here. It will be interesting to see if this slightly more complex version of the model can be used to address additional patterns in the empirical data (Grimm et al. 2005). If so, it might be able to teach us something the null version could not. Research programs built on simple exploratory agent-based models can be used in this way to generate new archaeological inferences and to build behavioral interpretations from the null-up.

6 Conclusion: Towards an Experimental Ethnoarchaeology

The title of this paper may be provocative, but it is not naïve. Experimental archaeology and ethnoarchaeology have proven useful separately, but what if we could combine them in an effort to build even better archaeological inferences? Consider what combinatorial effect might be gained by doing so. By coining the term *experimental ethnoarchaeology* I am not suggesting that we drop an experimental group of tropical foragers in the Arctic Circle so that we might first directly observe the assemblages they produce in a different setting and then compare them to assemblages produced by a control group back on the equator. This is a ludicrous proposition. Rather, I am arguing that exploratory agent-based models can provide a different kind of behavioral laboratory, one in which archaeologists can experiment with artificial societies by observing them in a number of different behavioral and/or ecological scenarios. Such ethically acceptable experiments allow archaeologists to rerun the tape of history, learn about the nonlinear dynamics of the evolutionary ecological models they create, and possibly discover something new about the past behaviors in question by testing hypotheses informed by an understanding of the model's dynamics rather than simply matching simulated data to observed data. Peck (2004) recently described how this type of modeling approach benefits other historical sciences, like ecology and evolutionary biology, and I feel it is equally relevant for use in archaeology.

In sum, the aim of this modeling approach is neither to describe nor to imitate details of the one true tape of history, for both are impossible goals. Rather, it is to explore a wide range of possible explanations, and to use an understanding of patterns found in artificial archaeological data, collected from controlled, repeatable experiments, to formulate expectations that can be tested with archaeological data collected from the field. One can use agent-based models in this way to build archaeological inferences from the null-up. When combined with the exploratory approach described here, archaeological agent-based models can help us take the crucial and necessary step from the realm of vague, untestable just-so stories to that of explicitly-defined, hypothesis-generating tools.

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