Chapter 4
Exploring Behavioural Terra Incognita with Archaeological Agent-based Models

Agent-based models are of the greatest utility when employed as behavioural laboratories in which archaeologists can explore the non-linear dynamics of artificial societies and their depositional processes by experimenting with a wide range of initial conditions and alternative histories. This approach differs from that which employs agent-based models as simulators, which paradoxically attempt to emulate the very behavioural processes under study. After discussing three deficiencies of the emulation approach, a few lessons are drawn from an ongoing project that employs an agent-based model strictly as an exploratory tool for learning more about Lower Paleolithic archaeological landscape formation from the ‘null-up’. One lesson learned from this heuristic modelling research is that, even in cases where hominin agents lack the ability to transport food resources to central places, ecological patchiness can structure their simple foraging behaviours such that the artificial archaeological landscapes they create display the same spatial signature that characterizes Oldowan archaeological landscapes.

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More than a decade ago, agent-based models found their way from computer scientists who were interested in artificial life to archaeologists who were interested in understanding the past. Since then, the technique has been used in a wide variety of archaeological applications, ranging from East African Plio-Pleistocene hominids (Premo 2005; 2006) to small-scale agriculturists in the U.S. Southwest (Dean et al. 2000; Kohler et al. 2000). For the most part, the archaeological community has met this initial round of agent-based applications with a healthy mix of enthusiasm and skepticism, but unfortunately many archaeologists still view agent-based models as a hybrid of Virtual Reality and role-playing video games (Bawaya 2006). I fear that, if left uncorrected, this misperception might lead to a consensus that, while agent-based models might be useful for illustration, they cannot be trusted for enquiry-based exploratory research, when in reality nothing could be further from the truth. This paper explains why archaeological agent-based models should be used principally for exploration and not for illustration, and it provides an example of how this kind of research can be done.

As the name implies, agent-based models make use of software objects called agents. Agents are specified by means of object-oriented programming languages (Java, Objective-C, etc.). These autonomous software entities are equipped with limited means to both perceive and react to aspects of their environment on an individual and usually goal-directed basis. Each agent ‘decides’ when and how to act by continually

1. See Kohler & Gumerman 2000, and Beekman & Baden 2005 for many other examples.

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comparing the values of its internal state variables to desired, optimal, or ideal values. Because internal values are derived from physical and social environmental surroundings, agents’ actions are ultimately a response to their environment. Agents also communicate with each other via messages.

In some agent-based models, a single agent interacts with an environment through simulated time (Brantingham 2003; 2006). In others, hundreds, thousands, or even millions of agents interact with an environment and with each other, thereby forming an artificial society (Epstein & Axtell 1996; Lansing 2002; Kohler et al. 2005). Whereas the conditional rules that each agent follows may be quite simple (e.g. if body temperature exceeds an acceptable threshold, then move to a cooler locale as efficiently as possible), the aggregate outcome of a population of agents may be difficult to predict (e.g. the migration of a group of agents to a cooler locale might take a direction not allowed to any individual agent). Such emergent properties are generated from the bottom-up in agent-based models. They arise from individual agents’ actions just as the global properties of an actual society emerge from the actions of, and interactions between, individual persons. Artificial societies often exhibit emergent collective properties that can be strikingly similar to those displayed by real societies. The ability to study non-linear dynamics generated from the bottom-up not only distinguishes agent-based models from top-down, deterministic models, but it also makes them especially attractive to social scientists (Epstein & Axtell 1996).

Archaeology has had a long, fruitful relationship with deterministic formal models. For example, linear programming models were once very popular among those interested in modelling hunter-gatherer foraging decisions (Reidhead 1979). However, most agent-based models are fundamentally different from deterministic mathematical models because a) they allow for populations of heterogeneous agents, b) they can be spatially explicit, and c) they incorporate stochasticity and historical contingency, so that one can study behavioural tendencies rather than laws (Kohler 2000; Premo 2006). The most important and unique features of the methodology can be summarized in one brief sentence: agent-based models make possible the study of non-linear cultural dynamics that emerge from historically contingent actions of heterogeneous agents interacting in space. Thus, one can use them to explore the kinds of biocultural evolutionary dynamics that are of ultimate interest to archaeologists of all stripes.

A tale of two approaches: emulation and exploration

‘Simulation’ is a synonym for ‘imitation’; to simulate is to mimic. However, while the terms ‘computer simulation’ and ‘simulation model’ are freely used in archaeological literature, no computer model truly imitates, mimics, or emulates every detail of reality. This limitation can be used to an advantage. Models encode our simple concepts about how the world works. This allows us to explore systematically our ideas about the past, independently of the empirical archaeological data against which we must continuously test theory (van der Leeuw 2004). Despite the fact that this built-in exploratory lever is inherent to all agent-based models, there is a strong temptation for archaeologists to emulate only those scenarios which they think were most likely responsible for the formation of empirical archaeological datasets, often at the expense of looking for other plausible alternatives.

There are many uses for models that simulate real phenomena (i.e. simulators), but such models include two important caveats. First, simulators work well only if one knows almost everything there is to know about the phenomenon of interest a priori. For example, the extremely realistic flight simulators used to train new pilots are effective because they incorporate so many of the details that are known to be involved in flying an airplane. The same cannot be said of our simulation models of past behaviours and environments, because our prior knowledge of important variables is at best terribly incomplete. Obviously, it is impossible to create a model that accurately emulates something one does not completely understand. I cannot precisely emulate Homo habilis behaviours in the same sense that Wilbur
and Orville Wright could not possibly have created a usable flight simulator for an F-16 fighter pilot. In both cases, we simply lack the knowledge needed to provide an accurate imitation.

Second, simulators are usually employed as teaching devices, not as discovery tools. In the example above, flight simulators are employed to teach less experienced pilots what other pilots have already learnt about flying airplanes. In archaeology, however, the function of simulation is often just the opposite. Our best simulation models function as a heuristic devices, designed to help one learn more about the deficiency of one's ideas about an unknown phenomenon or systemic process, or, as Zubrow (1981: 143) put it over a quarter of a century ago, 'not to solve problems but to create new problems and view old ones in new and interesting ways'. However, if the main goal of an archaeological agent-based model is to reproduce some characteristic of an archaeological assemblage (i.e. to act as a simulator), it cannot help but reiterate what one already 'knows'. As a result, simulators will reinforce a small subset of ideas about the past without first testing them against empirical data or comparing their expectations to those of simpler alternatives, and they will rarely illuminate new problems or cast old ones in a new light.

The emulation approach to archaeological agent-based modelling suffers from at least three serious logical deficiencies. First, although one might create a model with the good intention of making it as 'realistic' or as well-supported by ethnographic observations as possible, the fact remains that an infinite number of conceptual models can reproduce some characteristic of any archaeological phenomenon. In most cases, many different models can yield nearly identical outcomes, each of which matches the empirical expectation equally well. This many-to-one relationship is due to the principle of equifinality, which states that, in open systems, any given final state, or 'result', can be reached via more than one possible path and/or from more than one set of initial conditions, or 'starting points'. Equifinality prompts a difficult question: when the observed outcomes (i.e. simulated data) of several different models match the expected outcome (i.e. empirical data), which is the preferred model for explanation? One answer to this question is 'none', because they are all equally relevant. Another common answer is the model that explains the greatest amount of variation in the empirical data. I think a better answer than either of these is the simplest model, because it provides the best place to start the heuristic process. It is best to start this process with simple models because they include far fewer of the unnecessary assumptions that plague more complicated explanations. This does not mean that the simplest model will always provide the most comprehensive, or even the most accurate, explanation possible; Ockham's razor is not a magic wand. For this reason, one should not stop the heuristic process after only one model. Alternative versions will vary both in the complexity and the number of assumptions they include. Not only is this acceptable, it is to be expected. However, the decision to use more complicated versions to inform archaeological interpretation should be based not on the perception that they are 'more realistic', but on the fact that they provide hypotheses that cannot be disproved by empirical data when those provided by the simpler version can be. Finally, we need to keep in mind that, unless alternative models are created systematically from a null or neutral version, the task of deciphering which is simpler is non-trivial.

Second, the act of tuning variable values to match the conditions of just one scenario can lead to a false sense of explanation by emergence, which I call the Sirens of Titan fallacy. Kurt Vonnegut, Jr. explores the notion of free will in his second novel, *The Sirens of Titan*. One of its main characters, named Winston Niles Rumfoord, has been cursed to a life of unrest: he and his dog are beamed across the solar system and through time at just a moment's notice. During the course of his travels, Rumfoord meets an interesting robot named Salo, who has been marooned on Titan for over 200,000 years. From back on his home planet of Tralfamadore, Salo's superiors have repeatedly assured the shipwrecked voyager that the small part needed to repair his hobbled space ship is on its way. However, they communicate with Salo in a most unusual way:
It was through his viewer that [Salo] got his first reply from Tralfamadore. The reply was written on Earth in huge stones on a plain in what is now England. The ruins of the reply still stand, and are known as Stonehenge. The meaning of Stonehenge in Tralfamadorian, when viewed from above is: ‘Replacement part being rushed with all possible speed’. Stonehenge wasn’t the only message old Salo had received (Vonnegut 1959: 271).

In this story, many of humankind’s architectural achievements—the Great Wall of China (‘Be patient. We haven’t forgotten about you.’), the Golden House of Nero (‘We are doing the best we can.’), and the Palace of the League of Nations in Geneva (‘Pack up your things and be ready to leave on short notice.’)—were actually intergalactic messages to a stranded alien (Vonnegut 1959: 271-272). Even more disturbing is that human behaviour had been ‘scripted’, or determined from the top-down, by the Tralfamadorians, who had both the will and the power to influence occurrences on Earth. Until Rumfoord discovered Salo’s deep secret, only one party (the Tralfamadorians) was privy to the fact that human behaviour was being ‘tuned’ from the top-down. To any other intergalactic observer, the development of human civilizations would have looked like an interesting emergent property. Those observers would have been fools, however, because the Tralfamadorians kept their human agents to a deterministic script. Unfortunately, the same can be true of agent-based models designed to emulate one preconceived notion of what happened in the past. In many of these cases, it is impossible for casual observers to discern between two possible explanations for the observed outcome: a) the collective behaviour of interest is predetermined by a small set of ‘tuned’ variables, or b) the collective behaviour of interest emerges from interactions of individuals who make their decisions independently of any script. As a general rule, one should avoid models that make possible the interpretation that important collective behaviours are emergent when they are in fact predetermined.

Third, emulation is not explanation. Engineers have built bipedal robots that are capable of moving about an arena on two ‘legs’. Some of these engineers might argue that the process of constructing these robots has taught them something new about bipedalism, but far fewer would argue that by simply emulating a form of bipedalism with machines, they have gained a suitable explanation for how and why the earliest hominins evolved their unique bipedal gait. The same is true if one merely emulates preconceived notions of past behaviours in agent-based models. Simply emulating a particular view of the past in silico does not an explanation make. Further, very little new knowledge is gained from an agent-based model built expressly to imitate an archaeological outcome. Such exercises may demonstrate programming skill, but they will rarely teach us anything new about the behavioural processes of interest. Much like the engineer, who cannot be certain that her mechanical solution in any way ‘explains’ something about how bipedalism evolved in hominids millions of years ago, a programmer cannot be certain that any single simulation run—especially one designed to replicate a particular set of archaeological data (i.e. a simulator)—explains anything at all about the real biosocial processes that played some part in the formation of a real archaeological landscape. Do not despair, for it does not have to be this way. In my opinion, archaeologists interested in using agent-based models as tools to better inform their interpretations should refrain from attempting to explain the past by simply emulating processes which they do not fully understand; instead, they should employ an exploratory experimental design—one which allows them to replay the so-called ‘tape of history’ (Gould 1989) as they explore how a wide range of plausible environmental and behavioural scenarios affects the distribution and composition of artificial archaeological assemblages over the course of thousands of simulation runs.

In discussing the importance of contingency in understanding evolutionary history, the late Stephen J. Gould proposed an interesting thought experiment (Gould 1989). Imagine being able to pick any point in the past—the Cambrian explosion, the last glacial
maximum, etc. History could be restarted and certain subjects observed from that point. One could then watch different plots unfold, depending on the contingencies of history. Gould notes that

[...] 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).

Unlike a videotape of *The Natural*, which repeatedly and faithfully depicts an injured Roy Hobbs launching an improbable home run into the stadium lights and rounding the bags one final time under a cascade of sparks and cheers, the divine tape player can show different evolutionary outcomes, depending on both the sequence and the types of unique historical events (e.g. changes in climate, meteorites, epidemics, off-speed pitches, etc.). Thus, if *The Natural* were replayed in Gould’s cosmic tape player, Hobbs might strike out.

Gould’s thought experiment illustrates the importance of historical contingency, a component of cultural and biological evolution that is often downplayed by those concerned with uncovering universal laws. But it also introduces a novel research methodology to everyone involved in the historical sciences. Archaeologists are interested in retracing the trajectories of past societies, in hopes that a better understanding of past cultures will ultimately contribute to a more nuanced appreciation of our own species’ place in the natural world, as well as how our decisions will affect the future. In this endeavour, we have access to two types of empirical data sets. The first is an exceedingly incomplete and biased subset of all of the physical matter (fossils, stone tools, ancient DNA, etc.) deposited during the one and only run of the tape of history. The second is composed of that which we can observe in the current (unique) outcome of the evolutionary tape of history—the details of life as it exists today.

Considering these remains and the selective forces that operated on the organisms responsible for them prompts an important question: how likely is the current scene—life as we witness it today—given all reasonable historical possibilities? For instance, given our empirical observations of the current scene, we know that humans are bipedal. But what is the likelihood that bipedalism would have evolved in our lineage given a slightly different historical scenario, perhaps one that involved a slightly different climate? Of course, archaeological landscapes are also open to the same kinds of questions. For example, how do qualitatively different behaviours affect the spatial distributions of cultural material, and would the archaeological patterns that we exhume have been sensitive to small changes in these behaviours? Answers to these questions lie in discovering the likelihood that currently observable ‘outcomes’ would also occur in other plausible social and biological environmental settings. This is impossible to do in reality because the real tape of history cannot be re-run. However, this feat can be realized by looking for regularities in the behaviour of agent-based models of complex adaptive systems under a variety of experimental conditions (Lansing 2002; Premo 2006).

In summary, emulation *in silico* cannot prove that our ideas about the past are correct. To believe otherwise is to fall victim to the silicon siren’s song. But, by allowing the user to control initial conditions while playing out multiple alternatives—to replay Gould’s tape of history hundreds or thousands of times—agent-based simulation can provide a way to explore the archaeological implications of a wide range of plausible scenarios and alternative histories. This is not to say that such exploratory models can be used to support any interpretation, regardless of how far-fetched or divorced from empirical data that interpretation might be. To the contrary, one is able to eliminate unfit propositions using this modelling approach precisely because it allows one to test often ill-defined alternatives in a more rigorous setting. This approach also allows us to see when common assumptions and expectations lead to implausible archaeological outcomes. This experimental design yields fruitful models that permit the exploration of multiple ‘what if’ scenarios, which Gould (1989) calls ‘plausible channels’ and Gumerman & Kohler (2001) call ‘alternative cultural histories’. By
contrast, the emulation approach yields models that are engineered to produce the outcomes to which we are predisposed and, as a result, stands to teach us very little that we did not already ‘know’ to be true.

Exploring behavioural terra incognita in the Lower Paleolithic

[...] in pursuing the archaeology of the very remote past we are exploring behavioural terra incognita. If we are to avoid simply creating our origins in our own image, we have ruthlessly to expose all important propositions, however obvious seeming to potential falsification (Isaac 1983: 16).

This candid statement by Glynn Isaac outlines a simple, yet under-appreciated, approach to Paleolithic archaeology. Following this advice, I have reported elsewhere on a recent attempt to falsify some fundamental assumptions concerning the formation of Plio-Pleistocene archaeological landscapes (Premo 2005; 2006). In the spirit of experimentation and exploration, I used a null model to question whether some previously held behavioural assumptions are logically necessary to produce spatial signatures in artificial archaeological landscapes that are similar to those documented empirically in East Africa. Of particular interest is whether food sharing at central places was necessary for the formation of the so-called ‘scatter and patches’ archaeological landscapes that are characteristic of the Lower Paleolithic record in East Africa (Kroll & Isaac 1984). Many early studies relied heavily upon observations of living humans to address early hominid food sharing, but extant and historically documented hunter-gatherer groups represent a small subset of possible forager societies, each bound by its own historical, economic, and political contexts. Equally important is the fact that modern hunter-gatherers are members of an entirely different hominid species than those living during the Plio-Pleistocene. For these reasons, the referential method of using modern hunter-gatherer behaviours as direct analogues for those displayed by earlier hominids has fallen out of favour with many paleoanthropologists.

In contrast to previous referential studies, I employed an agent-based model, called the Simulated Hominid Altruism Research Environment (hereafter SHARE),2 as a behavioural laboratory to investigate how a wide range of experimental behavioural and ecological scenarios affect artefact clustering in artificial archaeological landscapes. SHARE’s behavioural assumptions are much simpler than those of earlier explanatory frameworks, many of which presumed that Plio-Pleistocene hominids habitually employed central place foraging techniques (Leakey 1971; Isaac 1978; Lovejoy 1981; but see Binford 1981; 1987; Isaac 1983; Potts 1988 for some earlier examples of those that did not). Central place foraging, which is commonly observed among contemporary hunter-gatherers, involves delaying consumption of procured foodstuffs until they have been transported back to a prearranged meeting place, where they are often shared with others who have congregated there. This modern human behaviour was often attributed to early hominins as a way to explain the formation of the ‘scatter and patches’ distribution of Oldowan material. Although subsequent research has tempered the precocious interpretation that ‘patches’ of Oldowan artefacts are the by-products of hominin activities centred on central places, this notion has been very influential in prior Lower Paleolithic reconstructions, despite the lack of empirical archaeological evidence that independently demonstrates that central place foraging was employed regularly by hominins during the Oldowan.

With SHARE, I am using a bottom-up model as a behavioural laboratory. More specifically, SHARE is a spatially-explicit agent-based model that explores how ‘scatter and patches’ archaeological landscapes could have been produced by Plio-Pleistocene hominins under various behavioural and ecological conditions. The hominins in the model are independent agents that can be equipped with different behaviours and dropped in a

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2. SHARE is programmed in Objective-C, and makes use of Swarm libraries (see http://www.swarm.org).
range of ecologically patchy food resource distributions. It is important to emphasize that SHARE is neither VR nor a role-playing video game. What little SHARE has in the way of visualization is highly effective, but laughably crude [Plate 1]. In fact, it would not be an exaggeration to say that, beyond serving a valuable use in visual debugging (Grimm 2002), SHARE’s visual interface is completely superfluous (this statement certainly is not true of VR). But this is of little concern to my behavioural research agenda, because eye-popping visual effects are far less important than the artificial archaeological data collected during each simulation run. The raw spatial data describing artefact density across space—not fancy visual displays—can be used to address the research question concerning the extent to which resource patchiness affects the spatial structure of an artificial archaeological landscape.

SHARE’s results demonstrate the powerful role that resource patchiness can play in structuring the archaeological remains of a population of socially inept foragers who do not employ central place foraging techniques of any kind or share food with others.

Fig. 2. Local Moran’s $I_i$ quantifies the effect of ecological patchiness on the spatial structure of archaeological landscapes. Each column presents three looks at the spatial structure of a different artificial assemblage: A. raw number of artifacts per cell, B. $I_i$ z-scores, and C. histogram of $I_i$ z-scores. Note that each appears with some summary statistics. Underlying ecological patchiness increases from left to right: 1. patch size 42, gap size 0; 2. patch size 10, gap size 4; and 3. patch size 4, gap size 6.
in need. **Fig. 2** presents the artificial archaeological landscapes of three different simulation runs at three different levels of ecological patchiness, ranging from one megapatch on the left (not patchy) to a very patchy environment on the right. The integers in the raster surfaces presented in Row A of **Fig. 2** represent the number of artefacts deposited per cell.

Using only the naked eye one can detect the patterning in archaeological assemblages that is caused by increasing ecological patchiness. But to analyze this clustering quantitatively, local spatial statistics are required. Elsewhere, I have introduced archaeologists to local spatial autocorrelation statistics, including local Moran’s I ($I_i$) (Premo 2004). Local Moran’s I can be used to identify localized hotspots of similar values, whether low or high. Positive $I_i$ z-scores indicate that the target cell is similar to its spatial neighbourhood, whereas negative scores indicate that it is very different from its neighbours; a value near 0 means that there is no spatial autocorrelation at that scale. Although the raster maps of the standardized z-scores [**Fig. 2**, row B] seem to reflect an obvious trend from less to more patchy assemblages from left to right, the more reliable evidence for this trend comes in the form of quantitative measures of skewness and kurtosis [**Fig. 2**, row C]. Skewness characterizes the degree to which values are asymmetrically distributed around their mean. Positive skewness indicates a right-skewed distribution, which has an asymmetric tail extending toward positive values; while negative skewness indicates a left-skewed distribution, which has an asymmetric tail extending into negative values. Kurtosis, on the other hand, characterizes the relative flatness (or evenness) of a distribution as compared to a normal, bell-shaped distribution. Positive kurtosis indicates a relatively peaked distribution in which many values are concentrated in just a few bins. Negative kurtosis indicates a relatively flat distribution in which values are more uniformly distributed across the entire range.

When foraging in a large, homogeneous resource distribution, hominin agent movements yield a diffuse scatter of artefacts [**Fig. 2**, column 1]. Note that in this scenario, $I_i$ scores are distributed normally about 0. These are the very results one would expect to see under the assumption of a homogeneous archaeological distribution, one which lacks localized concentrations of artefacts. However, the other columns demonstrate that as food resource patchiness increases, so too does the structure of the resulting archaeological assemblages. As many generations of hominid agents search for energy via simple (i.e. not central place) foraging strategies, a consistently patchy resource distribution influences the spatial structure of the resulting archaeological landscape such that concentrations of artefacts accumulate in the vicinities of diachronically reliable food sources. As a result, the histograms in columns 2 and 3 are quite different from that in column 1. First, unlike the normally distributed $I_i$ z-scores of column 1, the histograms in the others are right skewed. Whereas the homogeneous spatial distribution yields relatively equal numbers of scores on either side of the mean and, as a result, a correspondingly low skewness value, the patchy spatial distributions produce far more positive $I_i$ scores than negative ones. This trend towards positive skewness is just what we would expect to see when archaeological distributions possess localized concentrations of similar values (i.e. patchiness). Second, as archaeological landscapes become patchier, one should expect their $I_i$ scores to be less evenly distributed across the range of possible values, a quality which can be assessed via a measure of kurtosis. As expected, the kurtosis value calculated for the z-scores of the patchiest spatial distribution [**Fig. 2**: 3C] is more than an order of magnitude greater than those calculated for either of the more diffuse spatial distributions.

So, how does this agent-based exploration better inform our ideas about Lower Paleolithic archaeology and Plio-Pleistocene hominin behaviours? For starters, it demonstrates that ecological patchiness can structure hominin agent behaviour such that artificial archaeological assemblages display the characteristic ‘scatter and patches’ distribution in lieu of central place foraging. Indeed, spatial data collected from a number of artificial assemblages created in different ecological scenarios demonstrate that foragers living in patchy environments need not display central place foraging.
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strategies in order to leave behind equally patchy archaeological landscapes (Premo 2006). Note that, if this agent-based model had merely emulated Lower Paleolithic archaeological landscapes with central place foraging agents, this finding could not have been reached, even though such a model probably would have yielded similar spatial data.

SHARE teaches us that in some ecological settings we may jettison some of the central assumptions of our highly detailed referential models without sacrificing much of their explanatory power. The spatial results demonstrate that, if minimal assumptions are made from the outset, many of the behavioural assumptions that have accompanied previous reconstructions are not necessary to explain the archaeological phenomenon of interest—at least in patchy ‘mosaic’ environments representative of those that become more prominent in East Africa throughout the Pliocene (Levin et al. 2004; Quade et al. 2004). According to this theoretical work, ecological patchiness alone can have a significant impact on the structure of the archaeological record left by solitary foragers. SHARE’s artificial archaeological results imply that in cases where Plio-Pleistocene hominins inhabited patchy ecological settings, it may not be necessary to invoke the more complicated behavioural explanations that involve central place foraging, division of labour, and male provisioning of nuclear families to explain the characteristic ‘scatter and patches’ archaeological landscapes they leave behind. Whether this simpler, theoretically derived alternative can be falsified requires that we return to the archaeological data, this time with different questions in mind and new hypotheses to test. This recursive movement between theory and data is the cornerstone of any heuristic modelling approach.

Conclusion

Exploratory models like SHARE force us to rethink the validity of our highly detailed behavioural reconstructions and their relationship to empirical archaeological data. SHARE does not ‘prove’ that central place foraging had no influence on the formation of empirical archaeological landscapes. However, it demonstrates that in certain ecological scenarios even simple foraging strategies, which do not include food-sharing at central places, can yield patchy archaeological distributions. The take-home message here is not that Plio-Pleistocene hominids were asocial, solitary foragers (itself, a tactful assumption made for the sake of the null model). Rather, it is that previous paleoanthropological reconstructions probably include a number of behavioural assumptions that are not necessary to explain important spatial signatures of Lower Paleolithic archaeological landscapes in patchy environments. If we avoid making these assumptions, at least until systematic testing has proven them necessary, we might allow ourselves to find empirical archaeological support for simpler alternatives that otherwise would not receive consideration.

Incorporating a more rigorous, theoretical modelling program in paleoanthropology—one that is founded on Glynn Isaac’s advice to expose our propositions to potential falsification—will prove enormously fruitful. One major goal of such a program is to build archaeological inferences of Lower Paleolithic behaviour from the ‘null-up’ via systematic experimentation with artificial societies. This approach provides a significant departure from that which borrows inferences from ultimately unrepresentative sources in hopes that they will apply in some essential way to hominins that lived over two million years ago. Agent-based models, designed with exploration and experimentation—not emulation—in mind, provide powerful tools for theory-building and, ultimately, for explanation, as researchers in other disciplines have already noted (Grimm et al. 2005). After all, interesting discoveries about the past are made possible by exploring different plausible behavioural and environmental scenarios and by testing new hypotheses, not by imitating the status quo in silico.
Bibliography


