

Chapter 14: Spatial Agent-Based Modelling

Mark Lake

Abstract

Archaeologists were among some of the earliest users of agent-based modelling, but recent years have undoubtedly seen a surge of interest in the use of this technique to infer past behaviour or help develop new theories and methods. Although ABM software is much easier to use than it was even 20 years ago and sufficiently powerful computers are more readily available, the success of a modelling project is still largely determined by decisions made about the purpose and design of the model, and the subsequent experimental regime. This chapter guides the reader through those key issues. It covers epistemological topics such as the role of the model in a wider project, the trade-off between realism and generality, the idea of generative modelling and the importance of adequate experimentation. It also discusses technical issues such as options for the integration of ABM and GIS, and even the dangers inherent in poor design decisions about the scheduling of agent behaviour.

Introduction

Spatial agent-based modelling (ABM) is a method of computer simulation that can be used to explore how the aggregate characteristics of a system—for example a settlement pattern, population dispersal or distribution of artefacts—arise from the behaviour of artificial agents. In archaeological ABM the agents are typically individual people or social units such as households. Agent-based modelling is often presented as part of the toolkit of *complexity science* (Beekman and Baden 2005, Epstein and Axtell 1996), but it is a very flexible method which can be used in projects informed by many different theoretical perspectives.

It should be noted that while the vast majority of agent-based models used in archaeology are explicitly spatial, the representation of space is not a *necessary* feature of ABM (see e.g. Ferber 1999). Moreover, many of the issues that arise when using explicitly spatial ABM are essentially the same as those that apply to the use of raster GIS, or various forms of statistical spatial analysis. For that reason, this chapter focuses in issues which are specific to the use of ABM, most of which are relevant irrespective whether the model is spatial. It is therefore strongly recommended that this chapter be read alongside others in this handbook. Chapters 2, 3, 7 and 19 may be particularly relevant to the task of preparing spatial input data, while chapters 4, 6, 8, 9, 21 and 24 discuss methods that may be relevant to the statistical analysis and presentation of spatial simulation outputs.

The primary purpose of this chapter is to explain the choices that must be made when designing, building, experimenting with and disseminating an ABM. Readers seeking a practical tutorial complete with sample models and code should consult Railsback and Grimm's excellent (2012) *Agent-Based and Individual-Based Modelling: A Practical Introduction*. Readers who are interested in the history and theory of ABM in archaeology will find up-to-date reviews in Cegielski and Rogers 2016, Lake 2014 and Lake 2015. Additional discussion of the relationship between ABM and archaeological theory can be found in Aldenderfer 1998, Beekman and Baden 2005, Beekman 2005, Costopoulos 2010, Kohler 2000, Kohler and van der Leeuw 2007a, McGlade

2005 and Mithen 1994. Useful textbooks on agent-based modelling include Grimm and Railsback 2005 (aimed at ecologists), the rather briefer Gilbert 2008 (aimed at sociologists) and Ferber 1999 (aimed at artificial intelligence researchers and computer scientists).

Agent-based models in archaeology

Archaeologists were arguably using the forerunners of ABM as far back as the 1970s (Lake 2014), but there has undoubtedly been an explosion of archaeological interest in ABM since the publication of Kohler and Gummerman's (2000) influential collection of agent-based models, *Dynamics in Human and Primate Societies* in 2000 (Lake 2014), especially in the last ten years (Cegielski and Rogers 2016).

Characteristics of archaeological ABM

The tens of ABM now published in the archaeological literature (see Cegielski and Rogers 2016 and Lake 2014) range in complexity from models that barely meet the minimum textbook definition of an agent-based model (Ferber 1999, pp.9–10) but were implemented using ABM software (e.g. Bentley et al. 2004), through relatively simple abstract models of one or a limited number of processes (e.g. Crema and Lake 2015, Premo 2007), to much more complex models seeking greater realism in their portrayal of human society (e.g. Aubán et al. 2015, Kohler et al. 2012a, Wilkinson et al. 2007).

The Long House Valley ABM, presented as a case study later in this chapter, illustrates many of the features of a modern spatial ABM (fig. 14.4). This agent-based model was built to explore the relationship between climatically determined resource availability, settlement location and population growth in Long House Valley, Arizona in the period A.D. 400–1450. The agents are individual Puebloan households which are endowed with rules by which they choose where to settle in Long House Valley in order to grow sufficient maize to survive. The model is explicitly spatial because these agents inhabit a geographically realistic model of Long House valley, comprising GIS-style raster maps of maize-growing potential and the location of water sources. The maize-growing potential for each hectare in the valley was determined by detailed palaeoenvironmental research. The simulation progresses in yearly steps, at each of which the resource availability is modified according to a high resolution time-series estimates of rainfall. At each time-step settlements grow, fission, relocate or collapse depending on the ability of individual agents (the households) to grow sufficient maize to support their ongoing maintenance and reproduction. Over time, repeated individual household decision-making and reproduction produces a changing aggregate settlement pattern and population size, which can be compared to observed and proxy evidence in the archaeological record.

Although the Long House Valley Model is among the best known archaeological spatial ABM (see Kohler et al. 2005 for a popular account), it is by no means exhaustive in terms of the kinds of entities, relationships and processes which can be captured in an ABM. Particularly notable extensions, each considered in turn, are sociality and cognition, evolution, environmental change and virtual reality.

- *Sociality and cognition.* Archaeologists have increased the realism of human agents by incorporating aspects of social interaction. This ranges from agents learning from one another (Kohler et al. 2012b, Lake 2000a, Mithen 1989, Premo 2012, Premo and Scholnick 2011), through simple collective decision-making (Lake 2000a) to the exchange of goods (Bentley et al. 2005, Kobti 2012), group formation (Doran et al. 1994, Doran and Palmer 1995) and the emergence of leaders (Kohler et al. 2012b). Another way of increasing the realism of agents is to explicitly model learning and memory. These are a feature of a number of models of hunter-gatherer foraging, including Costopoulos' (2001) investigation of the the impact of time-discounting, Mithen's (1989, 1990) model of decision-making in Mesolithic hunting and Lake's (2000a) spatial ABM of Mesolithic land-use. The last of these extends to each agent having its own geographically referenced cognitive map of its environment (fig. 14.1).

<Figure 14.1 about here>

- *Evolution.* In ABMs built to explore change over longer periods of time it may be appropriate for the population of agents to evolve as a result of agent reproduction involving recombination or mutation of agent rules (or other attributes that are normally fixed for the lifetime of the agent). Examples include Premo's model of hominin prosociality (2005), Kachel et als' (2011) evaluation of the 'grandmother hypothesis' for human evolution, Lake's (2001b) model of the evolution of the hominin capacity for cultural learning and Xue et als' (2011) model of the extent to which tracking the environment too closely can be detrimental in the long term. There are also a number of ABMs which model the cultural transmission of traits across agent generations, for example Premo and Kuhn's (2010) investigation of the effects of local extinctions on culture change and diversity in the Palaeolithic.
- *Environmental change.* Many archaeological ABMs include environmental change. One option is external forcing, where the environment is altered over time to reflect palaeoenvironmental time-series data. For example, in the Long House Valley ABM (see the case study below) the maize yield changes over time following rainfall data, while in Xue et als' (2011) model changes in productivity are based on ice core data. Another option is to explicitly model the impact of agents on the environment. For example, early versions of Kohler et als' Village ABM reduced yields from continued farming (2000, 2012a), while recent versions also explicitly model the population growth of prey species such as deer (Johnson and Kohler 2012) thereby incorporating reciprocal human-environment interaction. Additionally, archaeologists interested in the *socioecological* (Barton et al. 2011) dynamics of long-term human environment interaction have coupled ABMs of human behaviour with geographical information systems or other raster models of natural processes such as soil erosion (e.g. Barton et al. 2010b,a and Kolm and Smith 2012).

- *Virtual reality*. Ch'ng and Stone (Ch'ng and Stone 2006, Ch'ng 2007, Ch'ng et al. 2011) have combined ABM and gaming engine technology to generate dynamic vegetation models for archaeological reconstruction and interactive visualisation of Mesolithic hunter-gatherers foraging in a landscape now submerged under the North Sea (fig. 14.2).

<Figure 14.2 about here>

Uses of ABM in archaeology

The general case for computer simulation in archaeology was initially advanced by Doran in 1970 and more recent discussion can be found in Cegielski and Rogers 2016, Costopoulos 2009, Kohler 2000, Kohler et al. 2005, Lake 2001a, 2014, Premo 2008 and Rogers and Cegielski 2017. Today, archaeologists typically use spatial ABM (and ABM more generally) for one or more of three main purposes.

- *Understanding long-term change*. The notion that archaeology has much to offer contemporary society as a science of long-term societal change and human-environment interaction (Johnson et al. 2005, van der Leeuw and Redman 2002, van der Leeuw 2008) has intellectual antecedents in the mid 20C programs of cultural ecology and sociocultural evolution (Kohler and van der Leeuw 2007a), but we now have better understanding of the importance of non-linearity, recursion and noise in the evolution of living systems, whether that is couched in the language of chaos (Schuster 1988), complexity (Waldrop 1992), evolutionary drive (Allen and McGlade 1987), contingency (Gould 1989), niche construction (Odling-Smee et al. 2003), or structuration (Giddens 1984). Since ABMs explicitly model and give causal force to the micro-level parts (agents) they are well suited to exploring how potentially non-linear long-term systemic change arises from the decision-making of agents interacting with and even modifying their physical and social environment (see Kohler and van der Leeuw 2007a and Barton 2013 for manifestos, Kohler and Varien 2012 for the history and role of simulation in one long-running socionatural study, and Beekman and Baden 2005 for a more overtly sociological perspective).
- *Inferring behaviour from the archaeological record*. ABM can be used in conjunction with 'middle range theory' (Binford 1977) to help infer what "organisational arrangements of behaviour" (Pierce 1989, p.2) and human decision-making (Mithen 1988) produced the observed archaeological evidence. Archaeologists usually make the connection between past behaviour and its expected archaeological outcome on the basis of "intuition or common sense, ethnographic analogies and environmental regularities, or in some cases experimental archaeology" (Kohler et al. 2012a, p.40), but computer simulation is particularly advantageous for this purpose when the candidate behaviours can no longer be observed and have no reliable recent historical record. Moreover, simulation makes it

possible to explore the outcome of behaviour aggregated and sampled at the often coarse grained spatial and temporal resolution of the archaeological record. Good examples of this are Mithen's (1988, 1990) use of ABM generated virtual faunal assemblages resulting from different Mesolithic hunting goals and Premo's (2005) spatial ABM of Pleistocene hominin food sharing which revealed that the dense artefact accumulations at Olduvai and Koobi Fora, long attributed to central place foraging, could alternatively have been formed by routed foraging in a patchy environment.

- *Testing quantitative methods.* The fact that computer simulation can be used to generate expected outcomes of known behaviour also makes it well-suited for testing the efficacy of other analytical techniques. The role of such 'tactical' (Orton 1982) simulations is to provide data resulting from known behaviour which can then be sampled in ways that mimic the various depositional and post depositional process which determine what evidence we eventually recover. By varying the behaviour and/or the subsequent degradation of the data it is possible to investigate whether the analytical technique in question is capable of retrieving a (typically statistical) 'signature' which is unique to the original behaviour. Examples include tests of measures of the quantity of pottery (Orton 1982), the efficacy of multivariate statistics (Aldenderfer 1981b) to differentiate functional assemblages, the ability of cladistic methods to reconstruct patterns of cultural inheritance (Eerkens et al. 2005), the relationship between temporal frequency distributions and prehistoric demography (Surovell and Brantingham 2007), the effect of field survey strategy in the recovery of data from battlefields (Rubio-Campillo et al. 2011), and the robustness of population genetic methods when applied to time-averaged archaeological assemblages (Premo 2014).

Method

Having decided on the purpose of an ABM, the next task is to determine what should be included and in what detail (system bounding), followed by how exactly they should be modelled (detailed design). After this it will be necessary to choose software to implement the model and, having implemented it, verify that it works correctly (in a software sense). As discussed below, creating a computer model can be informative in itself, but ultimately the purpose is to run experiments, which should be carefully designed according the purpose of the model and earlier decisions about system bounding and detailed design. Finally, the modeller should consider how to disseminate the model to promote reproducible research and the longer-term advancement of knowledge. Each of these major topics is discussed in turn.

Problem definition and system bounding

The different uses to which archaeologists put ABM potentially pose different requirements of a model, particularly the extent to which it should produce output that can be directly compared with measurable features of the

archaeological record. However, it is always important to be clear about which aspects of the system can be considered *known* and which are the *unknown* aspects about which new knowledge is sought. Deciding what to include in a model—system bounding—requires an awareness of epistemic issues which influence the capacity of a model to generate new knowledge (see Lake 2015 for a more detailed treatment).

- *Informative models are generative.* It is widely agreed (see Beekman 2005, Costopoulos 2009, Kohler 2000 and Premo 2008) that the explanatory power of a simulation model lies in the fact that it “must be observed in operation to find out whether it will produce a predicted outcome” (Costopoulos 2009, p.273). Models which must be run to determine their outcome are termed ‘generative’ (with respect to the phenomenon of interest). The challenge when building generative models is to avoid an infinite regress: imagine the complexity of a model in which social institutions emerge from the actions of individual people whose *self* in turn emerges from explicit modelling of their underlying neuropsychology, which is in turn modelled as an outcome of the replication and mutation of genes. The outcomes of a model like this might be so sensitive to chance events that it would effectively have little or no explanatory power and, in any case, it would very likely be computationally intractable. The solution is to ‘bracket’ or hold constant those aspects of the world thought to be causally distant from the question at hand. For example, in biology it is possible to win useful insights into cycles of mammalian population growth and collapse without modelling atomic vibrations within the biomolecules that make up muscle fibres. Even sociologists who reject the ontological reality of social institutions accept that for practical purposes it may be necessary “to assume certain background conditions which are not reduced to their micro dimensions” (King 1999, p.223). Ensuring that an ABM is “generative *with respect to its purpose*” (Lake 2015, p.25) requires a clear statement of what question(s) the model is intended to answer in order that it is clear what can be treated as known, and thus included in the model specification, and what is to be explained, and should therefore be left to be discovered by running simulations (see also Kohler et al. 2012a).
- *There is a trade-off between realism and generality.* In practice it is impossible to simultaneously maximise the generality, realism, and precision of models of complex systems (Levins 1966). Broadly speaking, one can have a generalised and probably relatively abstract model which fits many cases but none of them in every detail, or a more specific and probably more realistic model which fits just one or a few cases in greater detail. In the case of an ABM greater realism normally entails one or more of the following:-
 1. Capturing a larger number of different properties of the modelled entities. For example, does the environment contain woodland, or is it made up of several different tree species which have different calorific output when burned?

2. Modelling more of the relationships between different entities and so capturing a larger number of real-world process. For example, when a hunter kills prey, does that have no effect on the subsequent availability of prey, or does it deplete the prey population and, if so, does that in turn impact on future prey population growth?
3. Less commonly, visual realism in the sense of being rendered in a virtual reality.

There are different views on the relative merits of realism versus generality. Kohler and van der Leeuw (2007b, p.3) argue that “A good model is not a universal scientific truth but fits some portion of the real world reasonably well, in certain respects and for some specific purpose”, so not unsurprisingly suggest that the choice between realism and generality should be made according to the scope and purpose of the model. Others see a strong presumption in favour of simplicity (Premo 2008, Costopoulos 2017) on the grounds that: i) understanding requires reducing complexity to “intelligible dimensions” (Wobst 1974, p.151); ii) it is more parsimonious to discover how much complexity is necessary to explain the observed phenomenon than it is to assume it from the outset (Premo 2007); and iii) models which have not been finely honed to fit a particular case but can account for a greater diversity of cases have greater explanatory power because they allow one to predict what should happen in a wider range of circumstances (Costopoulos 2009).

Detailed design considerations

One of the advantages of ABM over other simulation paradigms is that it affords great flexibility in conceptualising and implementing the modelled entities and processes.

Environment

It is possible to build an ABM in which the agents are not explicitly situated in any kind of space, although in archaeology that is largely confined to tactical applications (e.g. Eerkens et al. 2005). Most archaeological ABM are spatial and the introduction of space requires consideration of three important issues.

- *Geometry.* Spatial ABM can have very different degrees of geometric specificity (Worboys and Duckham 2004). A purely topological network of agents explicitly models which agent is connected to which. Adding edge-weights to the network (see also Chapter 15, this volume) allows the modeller to provide information about the relationship between the agents (which could be the distance between them in Euclidean space, or a non-spatial property such as their similarity with respect to some trait). More commonly agents are located in Euclidean space, typically by placing them on a regular grid of cells akin to a GIS raster map. The grid can be ‘empty’, simply serving to locate agents with respect to one another, or it may contain values representing terrain or some other aspect of the environment. Gridded environments can be abstract, or they can be a geographically referenced representation of some part of the earth’s

surface. Often the opposite edges of abstract gridded environments are joined to form a continuous surface on a torus (doughnut), thereby avoiding edge effects such as a reduction in spatial neighbourhood (see e.g. Premo 2005).

- *Updating.* An important consideration is whether the agents' environment should be updated as the simulation runs. For example, in a simulation run for 100 years it would probably not be necessary to update terrain height, whereas it might be appropriate to denude a resource exploited by agents as and when they 'harvest' it. The latter would require a decision about whether, when and how the resource should regenerate. A decision of this nature will require careful thought about system bounding because it involves determining whether the resource can simply be 'reset' to some fixed value, or whether it should be set to a new value which is itself the outcome of explicitly modelling the process of regeneration. The latter blurs the boundary between agents and environment because in a sense the environment has acquired 'behaviour' whose outcome may not be known without running simulations—it too has become a generative phenomenon.
- *Input data.* The task of populating an ABM environment with appropriate values varies enormously in magnitude. An abstract model might use a synthetic environment of resource availability in which the absolute values may be arbitrary but perhaps the environment as a whole is characterised by a particular property, for example a specific amount of spatial autocorrelation (Lake 2001b). In this case a suitable grid of values can easily be created using GIS or statistical software (see Chapter 6, this volume). At the other extreme are ABMs with environments that represent the real world at some point in time. The necessary paleoenvironmental reconstruction is often a significant project in its own right, entailing both fieldwork and modelling (e.g. the case study below and also Barton et al. 2010a, Kohler et al. 2007, Wilkinson et al. 2007). Interpolating from sparse point observations of environmental data to a spatially continuous map of the distribution of a resource at an ethnographic-scale (say 20—1000m linear resolution) is likely to require use of ecological models such as that developed by Cousins et al. (2003), or other methods of downscaling such as that recently described by Contreras et al. (2018).

Agents

ABM is scale-agnostic, so agents can be any entity which can be treated as an individual in the sense that it acts as a cohesive whole in respect of the particular research problem (Ferber 1999). In archaeological ABM the agents are usually individual people, or groups of people such as households, so the most important design decisions usually concern agent goals, behaviour and learning (sociality is discussed later in the context of collectives). Note that many of the issues discussed here are not relevant to uncomplicated abstract models such as, for example, ABM's of cultural transmission in which agents simply copy traits from other agents (e.g. Lake and Crema 2012).

- *Attributes, states and behaviour.* Attributes are enduring traits which an agent possesses throughout its lifespan, for example whether it is male or female. In contrast, states change as a result of agent behaviour and decision-making (e.g. their location, energy reserves), the passage of time (age), or possibly external agent or environmental impacts (e.g. theft of resources). Whether a given trait counts as a fixed attribute or variable state depends on the framing of the research question. For example, consider two different ways of building an ABM to explore the transition from foraging to farming: endow agents with the decision-making capacity to change their preferred subsistence strategy (e.g. Bentley et al. 2005), or allow the relative proportion of lifetime foragers and farmers in the overall population of agents to change as a result of differential reproduction, inter-generational cultural transmission, or land-use competition (e.g. Angourakis et al. 2014). The former makes the subsistence strategy a state, the latter an attribute. Which of these is the right approach depends on the archaeological evidence, the duration of the transition and time-scale of the model, and the modeller's views concerning the primacy of individual human agency.
- *Goals.* Agents are autonomous in the sense that their behaviour is directed by their own goals, which may be different from those of other agents (Ferber 1999, pp.9–10). Ordinarily an agent's ultimate goals will be determined by the modeller, but its proximal (immediate) goal at any particular time during the simulation may be variable if has been endowed with the capacity for meta decision-making (see Mithen 1990). In evolutionary ABMs, in which agents differentially reproduce, the modeller usually determines a set of ultimate goals but does not specify which individual agent has which goal, except perhaps for the first generation. Evolutionary ABMs in which the suite of goals can evolve by recombination during agent reproduction are uncommon in archaeological ABM.
- *Rules.* An agent's behaviour depends on decision-making rules which determine how it 'thinks' it can best pursue its goals given the circumstances in which it finds itself. These rules are specified by the modeller (except in models where they can evolve), but if the model is generative it will be necessary to run the simulation to discover how the agents actually behave. Ordinarily agents are rational in the sense that their decision-making rules ensure a non-random relationship between their goals, circumstances and behaviour. Rationality in this sense requires that agents have some measure of the absolute or relative 'worth' of the actual or predicted outcomes of different behaviours—what biologists term 'fitness' and economists term 'utility' (Railsback and Grimm 2012, p.143). This terminology and the fact that many archaeological ABMs use insights from behavioural ecology (see Kohler 2000 and Mithen 1989 for arguments in favour) has led to criticism of agent decision-making rules on the grounds that they project modern rationality back into the past (e.g. Clark 2000, Cowgill 2000, Shanks and Tilley 1987 and Thomas 1991). There are two issues at stake here: i) is it appropriate to invoke a rationality grounded in modern evolutionary biology or neoliberal

economics, and ii) is it actually *necessary* to do so when using ABM. This debate was reviewed by Lake (2004), who argued that ABM can *in principle* accommodate alternative rationalities.

- *Agent prediction / learning*. In an ABM learning can take place at the level of individual agents and/or the system as a whole. The latter is discussed in the context of collectives. An individual agent can be said to learn when it:-
 1. Discovers what resources are present in the environment as it moves through it. Note that a cognitivist would require that the agent forms a representation of the environment that is separate from the environment itself—a good test of this is whether the agent can ever have incorrect knowledge of its environment (perhaps due to the subsequent actions of other agents).
 2. Forms a view about something that is not directly observable. For example, the likelihood of encountering a particular type of animal is not directly observable, but must be inferred from the number of actual encounters in a given duration and, as a result, different agents could end up with different estimates based purely on chance. The accuracy of this kind of learning in a changing environment depends on how much weight agents give to more distant events relative to less distant ones, where distance could be in either time or space or both (see Costopoulos 2001 and Wren et al. 2014).
 3. Copies behaviour or obtains knowledge from another agent. Note that use of the term ‘social learning’ to describe this is intended to emphasise the fact that such learning eschews direct observation of the environment, not that it necessarily entails a patterned (social) relationship between the agents involved (Hinde 1976).

The possibility of explicitly modelling learning means that ABM can be used to build formal quantitative models in which humans are *not* perfect all-knowing decision-makers (see Bentley and Ormerod 2012, Mithen 1991, Reynolds 1987, Slingerland and Collard 2012).

Collectives

Both sociologists (Gilbert 1995) and archaeologists (Kohler and van der Leeuw 2007a, Beekman 2005) have advocated using ABM to study the emergence of social norms and institutions from the beliefs and actions of individuals. Emergence is a thorny philosophical problem (see Bedau and Humphreys 2008) and readers are referred to Beekman 2005 and Lake 2015 for more detailed discussion of the issues as they relate to archaeological ABM. Basically, the concept of emergence raises two main questions in the social sciences. One is whether the apparently recursive relationship between individuals and society means that social institutions actually exert irreducible causal influence on agents (see Gilbert 1995 for an overview). The other question is whether the fact that human agents reason about the emergent properties of their own societies makes

emergence in human systems qualitatively different from emergence in physical systems (Conte and Gilbert 1995, Gilbert 1995).

In practice one can distinguish three kinds of 'collective' phenomenon in ABM:-

1. Robust population-level patterning in the interactions of individual agents who are not, however, aware of this patterning.
2. Patterned interaction in which agents are in some sense aware of the pattern and perhaps even adjust their behaviour accordingly. For example, an agent might consider itself to belong to a group of agents who share complimentary goals, but not actually engage in collective decision-making.
3. Agents contributing to and abiding by collective decision-making. Examples of this kind of strong collective can be found in archaeological ABM of hunter-gatherer (Lake 2000a) and small-scale agricultural societies (Kohler et al. 2012b).

The modeller must decide how far to pre-program collectives or whether to allow them to emerge. The first kind of collective can readily be obtained by true emergence, whereas the second and third types are more commonly (Railsback and Grimm 2012, p.210) scaffolded by programming agents with additional characteristics (such as a group ID) and/or programming the characteristics of the collective entities (for example specifying the possible states and behaviours of groups even before any agents actually belong to them). At the present time archaeological ABM typically offer either emergent collective phenomena, or collectives with some causal influence over agents, but not both (see Lake 2015 for a more detailed assessment).

Treatment of time

Modelling how a process unfolds over time requires decisions about the appropriate temporal intervals and the scheduling of events.

- *Temporal intervals and duration.* The temporal intervals (timesteps) should reflect the frequency and duration of the relevant agent decision-making and behaviour. It is not always necessary to calibrate a simulation in terms of real-world time: for example, a tactical simulation intended to help develop measures of drift in cultural evolution might have timesteps which are just abstract generations. The total duration should reflect the rate at which the outcomes of agent behaviour accumulate to produce detectable patterns, both in the simulation itself and in the archaeological record (if relevant). Note that the minimum temporal envelope within which changes in behaviour can be observed in the archaeological record will often be longer than the duration over which such changes are detectable in the simulation results. One of the advantages of ABM is that it can be used to investigate what the results of ethnographic-scale human behaviours might look like when time-averaged in the archaeological record (e.g. Premo 2014), that is to say, what the accumulation of material from multiple episodes of behaviour might look like when aggregated

across the minimum time-span that archaeologists can differentiate given the effects of post depositional processes and available dating techniques.

- *Scheduling.* An ABM can be event driven, in which case agents individually schedule their own activities (e.g. Lake 2000b), or programmed so that all agents undertake activities at the same set intervals. The latter scenario is much more common, but unless the ABM is being run on specialised parallel hardware, the simulation will proceed sequentially even if conceptually agents are considered to be undertaking activities at the same time. In this case is good practice to ensure that agents do not undertake activities in the same order at every timestep, so as to avoid arbitrarily advantaging or disadvantaging those that come towards the front or back of the execution queue. It will also be necessary to decide whether or not agents should be aware of the results of the behaviour of other agents who preceded them in the queue. As an example, agents who are unaware that other agents have already harvested a resource in the same timestep will base their decision-making on imperfect knowledge, so the question is whether perfect or imperfect knowledge better captures reality.

Implementation and verification

Computer hardware

Productive ABMs have been run on hardware ranging from laptops to high performance computers (HPC) offering hardware parallelism. Hardware requirements are a function of the complexity of the model and the rigour of the experimental design (see the next section). In many cases it is the latter which poses the greatest challenge—a simulation which completes in one hour becomes a different proposition if it is necessary to undertake 1000 runs for all possible combinations of three parameters which can each take ten values! Hardware evolves very rapidly, but one general point worth noting is that simply increasing the number of cores in a computer does not increase the speed of simulation unless either the software supports parallel execution of the code, or it is possible to arrange simultaneous execution of multiple different simulations.

Software platforms

Implementation of an ABM invariably requires some computer programming, so the modeller will either need to learn to program or collaborate with others who can. ABM can be implemented using a variety of programming languages and software, each of which has pros and cons.

- *General purpose programming languages* (e.g. C++, Java, Python). These might be a good choice if the modeller already knows the programming language and the model is relatively simple. An ABM written in a general purpose compiled language such as C++ is likely to run very fast, but on the other hand the lack of existing functionality may slow down development of a more complex model, especially if a graphical user

interface (GUI) is required and/or integration with GIS or statistical software.

- *Statistical/mathematical programming languages.* To judge from recent examples (e.g. Crema 2014, Crema and Lake 2015) statistical programming languages such as R are probably better suited to simpler abstract ABM, especially where a GUI is not required. Quantitatively inclined archaeologists may already be conversant with languages such as R, but the greatest advantage of this approach is the direct integration of the model into a powerful framework for the statistical analysis of the simulation results (see for example Chapters 4 and 9, this volume), which can greatly facilitate rigorous experimental design.
- *Dedicated simulation frameworks.* Dedicated simulation frameworks (e.g. Ascape, Mason, Repast Symphony, SWARM) may provide a ‘drop-and-drag’ graphical model building tool, but in most cases the modeller will end up writing at least some programming code using an object-oriented language such as Objective C, Java or Python. The main advantage of a simulation framework is that it provides code for functionality such as controlling the simulation, setting parameters, scheduling agents, drawing them on screen, logging results and often also exchanging data with other software such as GIS. The most popular frameworks are largely ‘paradigm agnostic’ in that they do not impose a particular concept of what constitutes an agent or how to model the environment. Additionally, some frameworks (e.g. Pandora, Repast for HPC) support implementing ABM on high performance computers. Taken together, these attributes make the popular simulation frameworks well-suited for implementing complex computationally intensive ABMs.
- *Integrated modelling environment.* An integrated modelling environment provides a ‘one-stop’ solution for implementing an ABM by providing a single GUI for writing program code, running simulations, visualizing and logging the results and even automating multiple runs with different parameters. The best known is NetLogo, which provides an excellent vehicle for learning ABM (Railsback and Grimm 2012 uses it) while at the same time being capable of supporting useful scientific experiments in archaeology (e.g. Premo 2014). Indeed, a particular advantage of NetLogo is the built-in support for sensitivity analysis, which facilitates and encourages the experimentation required to actually learn from an ABM. NetLogo was originally designed around a particular concept of agents and their environment and it may (probably rarely) be unnatural or perhaps even impossible to use it to implement a specific conceptual model.

Integrating ABM and GIS

Spatial ABM require spatial input data and produce spatial results, so a means of connecting to GIS is invaluable. Additionally, an ABM which explicitly models environmental processes, for example soil erosion, might benefit from access to relevant GIS functionality. The various methods of coupling or integrating ABM

and GIS are discussed at length by Westervelt (2002) and Crooks and Castle (2012), but are briefly sketched here.

- *Loose coupling* entails moving data between the ABM and GIS by saving and importing files that both can read, typically a real or de facto interchange format such as ESRI's shapefile and ASCII grid formats. The most popular simulation frameworks and integrated modelling environments provide the necessary functionality to achieve this kind of coupling, which generally occurs at the beginning and end of each simulation.
- *Tight coupling* involves one or both of two enhancements over loose coupling. One is that the ABM can directly access the GIS data in its native format by connecting to the geodatabase maintained by the GIS software. Avoiding the need to convert data into an intermediate format and/or write it to disk potentially increases the speed of data exchange, thereby facilitating the second enhancement, which is synchronisation of the ABM and GIS, usually so that the GIS can actually be used to modify the environment occupied by agents at intervals during the the simulation (e.g. Barton et al. 2015). Tight coupling of this nature generally requires that both the ABM and GIS can be controlled by a meta-program (typically a Unix shell script or Python script).
- *Integration* takes tight coupling one step further and dissolves the distinction between the ABM and GIS software by embedding one in the other. One option is to model environmental change by implementing the relevant algorithms within the ABM, even to the extent of treating aspects of the environment (such as woodland) as being made up of agents (individual trees). Another is to modify the GIS software to implement agent behaviour and dynamic updating of the GIS data (e.g. Lake 2000b); this requires that the GIS software has a rich scripting language or that its source code is available for modification (as with open source software).

Verification

Verification is the process of ensuring that the ABM program code correctly implements the conceptual model (Aldenderfer 1981a). Verification is not intended to determine whether the underlying conceptual model is a good model of the world, although it can sometimes reveal flaws of logic, typically where the conceptual model simply does not specify what should happen under certain circumstances. Readers should consult Railsback and Grimm 2012, Chapter 6 for practical advice about how to verify ABM program code.

Experimentation and analysis

Building an ABM can be said to have “conceptual utility” (Innis 1972, p.33) if it has served to “create new problems and view old ones in new and interesting ways” (Zubrow 1981, p.143). Nevertheless, the full potential of simulation is only realised if enough time and resource is reserved for extensive experimentation to generate an ensemble of ““what if” scenarios” (Premo 2008,

p.50) or “alternative cultural histories” (Gumerman and Kohler 2001). Moreover, devising a generative ABM capable of matching patterns in the archaeological record is not sufficient to prove that the modelled process is what actually caused that pattern. The basic problem is that of underdetermination or *equifinality*: the possibility that other processes might also be able to produce the observed pattern. Mitigating the risk of making false inferences by replicating the past for the wrong reason requires rigorous experimentation designed to answer a series of questions.

What is the impact of chance events?

Most ABMs are stochastic, meaning that one or more processes have a random component. Randomness might reflect genuine randomness in the real world, but it is usually included to create initial variability in the model and/or as a means of bracketing out unnecessary detail and avoiding an infinite regress in the processes that must be modelled (Railsback and Grimm 2012, p.201–2). For example, in an ABM of hunting, an agent might probabilistically encounter prey, not because the movement of prey is actually random, but to avoid modelling the decision-making of each prey animal while maintaining the realism of the relevant aspect of prey movement (the frequency with which prey are found in different parts of the landscape); in this case implementing probabilistic prey encounter may also reflect the fact that agents are uncertain about whether they will encounter prey. When incorporating random events it is important to choose an appropriate probability distribution: in this example a Poisson distribution would be appropriate (the probability of a number of events occurring in a given time period), but a uniform or normal distribution would better characterise variability in many attributes. Note, however, that drawing quantities from a normal distribution can potentially produce extreme values that would simply be impossible in the real world and although this will (by definition) be rare it could invalidate the model or even halt the simulation.

The impact of stochasticity on simulation results should be explored by running multiple simulations which are identical apart from the seed used to initialise the random number generator. In this way it is possible to build up an ‘envelope’ containing all possible simulation results and thus to determine whether chance alone is sufficient to produce different outcomes that support different substantive conclusions. It is difficult to provide a hard-and-fast rule for how many runs should be made, but one way of deciding is to observe the declining rate at which new results fall outside the existing envelope and then stop once this falls to a level which suggests any possible outcomes not yet observed will be extremely rare. Note that multiple runs should be made for each possible parameter combination (see next), so experimentation can rapidly become computationally demanding even if the model itself is relatively simple.

How sensitive is the model to parameter changes?

It is usually desirable to conduct multiple simulations, each with a different combination of parameters (fig. 14.3). There are three main reasons for this, each requiring a slightly different approach.

- *Dealing with parameter uncertainty.* If there is uncertainty about what parameter values best represent the state of the world in the past then it will be necessary run multiple simulations with different values in order to establish the likelihood of different outcomes (rather as for dealing with stochasticity). Note, however, that the likelihood of different outcomes can only be estimated if attention is paid to both the range of parameter values and the probability that they are correct, since proportionately more simulations should be run with the more likely parameter values. Consequently, the parameter values should be drawn from a distribution which reflects the nature of the uncertainty: for example a uniform distribution if all values are equally plausible, but perhaps a normal distribution if a certain value is most likely and more distant values increasingly unlikely.
- *Establishing what is possible.* If the aim is to establish what could have happened in history under certain circumstances then it will be necessary to investigate what outcomes are possible given different assumptions and starting points. As with the case of parameter uncertainty this requires multiple simulation runs made with parameter values of interest. However, since the aim is not to establish the likelihood of different outcomes there is no need to attach a probability to different parameter values.
- *Estimating unknown parameters.* The aim here turns the conventional approach on its head by making the parameter values the unknowns that are to be estimated by running simulations. The logic is to vary the parameters and discover what values most reliably produce simulation results that match the archaeological record. A good example of this approach is Crema et al.'s (2014) use of simulation to investigate what kind of cultural transmission best explains observed changes in European Neolithic arrowhead assemblages. Formal models of cultural transmission usually have population size (of 'teachers') and innovation rate as important parameters, but these values are rarely known with certainty and indeed are often quantities that the modeller would like to infer. Crema et al. adopted an approximate Bayesian computation framework in which they provided prior probability distributions for these parameters and then ran multiple simulations which collectively sampled possible combinations of parameter values. By comparing the simulation results to the observed changes in the observed archaeological data they were then able to provide posterior probabilities for the parameters, in other words, to infer which values were more or less likely than others given both initial knowledge and the results of the simulations.

<Figure 14.3 about here>

How sensitive is the model to structural changes?

The behaviour of a simulation model depends on the structure of the model (e.g. the agent rules) as well as parameter values and chance events. Given the problem of equifinality there is a case for comparing “alternative model scenarios” (Railsback and Grimm 2012, p.113) rather than simply conducting sensitivity analysis of just one model. Railsback and Grimm note that this is not yet common and is therefore a “less formalized and more creative” process (Railsback and Grimm 2012, p.306) because—unlike parameter values—alternative rules can not be drawn from some defined quantitative distribution, but must instead be chosen on the basis of theoretical understanding. For example, in a spatial ABM of foraging the modeller might swap the goal of maximising intake with that of what is technically termed ‘satisficing’ (obtaining sufficient calories). However, pursuing this example, it can be argued that making this change is as much a comparison of two alternative models as it is a test of the robustness of the original model. Indeed, there is a case for abandoning hypothesis-testing using single models in favour of ‘multi-model selection’ (Rubio-Campillo 2016), which also carries with it a subtle epistemic shift from attempting to discover if one model is true to attempting to discover which of the currently available models is ‘best’ (Burnham and Anderson 2002). Adopting a model-selection approach opens up the possibility of more formalised methods for choosing between models. Again, Crema et al.’ (2014) investigation of cultural transmission in European Neolithic arrowhead assemblages provides a good example of how this might be achieved in practice.

Can the model account for multiple patterns?

One way of increasing confidence that simulation results fit observed data for the right reasons—in other words, that the model is a good representation of reality—is to adopt an approach known as “pattern oriented modelling” (‘POM’; see Railsback and Grimm 2012, p.291 and Altaweel et al. 2010). The basic idea is that it is often relatively easy to ‘tune’ a model to replicate a single dataset comprising just one variable, but rather more difficult to replicate multiple datasets and/or multiple variables. Achieving the latter suggests that the model is ‘structurally realistic’. Railsback and Grimm (2012) provide an excellent introduction to POM, but a brief archaeologically oriented example serves to illustrate the concept. Mithen (1993) built a computer simulation in which human hunting impacted on the population growth of mammoths. Rather than simply attempt to replicate the decline in the overall mammoth population, he explicitly modelled the age structure of the mammoth population. This not only provided an additional point of contact with the archaeological record (one more readily available than overall population size) but also better captured the real-world causal dynamics—that it might matter whether or not humans hunted animals of reproductive age.

Dissemination and re-use

Archaeological knowledge advances not just by collecting more data, but by subjecting existing interpretations to new scrutiny. However, although much archaeological interpretation relies on the use of computers and complex

software, “their role in the analytical pipeline is rarely exposed for other researchers to inspect or reuse” (Marwick 2017, Abstract). There is growing awareness of the need to rectify this situation (see also Ducke 2013 and Rollins et al. 2014) and Marwick has recently applied to archaeology some principles of reproducible research that have emerged in other fields. In the specific case of ABM reproducibility requires the following.

- *Dissemination of the program code and input data.* Ideally it should be possible for other researchers to run the simulation, both to verify the published results and to explore other scenarios. Program code and data can be disseminated as ‘supplementary material’ hosted alongside published journal articles, placed on web-based hosting service such as GitHub, or perhaps better still, uploaded to a collective repository such as Open ABM (<https://www.openabm.org/>). The ABM program code should include inline comments to help others understand how it works and should be accompanied by information about the computational environment required to run it.
- *Documentation of the conceptual model.* Researchers may be able to infer many aspects of the conceptual model from the program code itself, but that presupposes that the program is actually an accurate reflection of the original modeller’s intention and, in any case, it is helpful to have further information about assumptions that have been made. The ODD (Overview, Design concepts, and Details) protocol has been proposed as a standard for describing agent-based models and ODD-style documentation has been incorporated into the NetLogo integrated simulation environment. The full specification can be found in Grimm et al. 2006 and Grimm et al. 2010, but here is the outline:
 - Overview** The purpose of the model (which aspects of reality are included and why?). What the entities are and how they are characterised? What processes are included and when do they occur?
 - Design concepts** For example, is the model intended to produce emergent phenomena? Does it involve individual or population-level adaptation? Does it include stochastic elements? What is the nature of any collectives?
 - Details** How is the model initialized? What are the external inputs? A fuller mathematical and/or verbal description of the model.
- *Documentation of the experimental design.* In order to reproduce and/or extend published results, other researchers will also need to know the exact range of parameters ‘swept’ during multiple runs. Any post-processing of the raw simulation output (for example the aggregation or averaging of agent state variables) should also be documented.

Case study

As noted above, the Long House Valley ABM (Dean et al. 2000, Axtell et al. 2002) is a well known archaeological model (Kohler et al. 2005) which illustrates many of the features of a modern spatial ABM (fig. 14.4). There are several reasons for drawing attention to this model as a case study. One is that it tackles the kind of research question (collapse of societies) that excites interest beyond academe and to that extent, at least, is therefore a good advertisement for the use of spatial ABM in archaeology. Moreover, and not unrelated, a version of the model (called “Artificial Anasazi”) is available as part of the standard release of the popular and easy to install NetLogo ABM software (Stonedahl and Wilensky 2010b). Consequently, the interested reader can quite quickly get to the point of running the model, experimenting with it and ultimately exploring and even modifying the code. Finally—and unusually—this model has a history (Swedlund et al. 2015) to the extent that it has been re-implemented and studied by researchers who were not part of the original modelling effort, and this includes an analysis of what actually causes the model outcomes ((Janssen 2009, Stonedahl and Wilensky 2010a)). This history of use is an instructive lesson in how to ‘do science’ with archaeological spatial ABM.

<Figure 14.4 about here>

Research question

Long House Valley, in northeastern Arizona, was sparsely occupied by hunters and gatherers until the introduction of maize at around 1800 B.C. initiated the gradual development of substantial permanent settlements and the Puebloan Anasazi cultural tradition. The valley was abruptly abandoned around A.D. 1300 and the population migrated elsewhere. A key question is what caused the abandonment and, in particular, to what extent it can simply be explained by the onset of climatic deterioration at circa A.D. 1270.

Three features of Long House Valley make it particularly suitable for the application of ethnographic-scale spatial ABM. One is that the valley is a topographically discrete entity (of) which, given the focus on agricultural subsistence, provides a natural ‘edge’ for the simulated world. The second feature is the availability of very rich and high resolution palaeoenvironmental data which make it possible to estimate the maize growing potential of every hectare in the valley annually from A.D. 400–1450. Third, the valley has been intensively surveyed, so there is relatively complete knowledge of the Puebloan settlement pattern, much of it dated by dendrochronology. Additionally, it is claimed that ethnographic studies of historic Pueblo groups can be used to parameterise aspects of the model, such as the nutritional requirements of agents.

Model design

The two main components of the Long House Valley model are the landscape and agents. The landscape is a 100x100m raster representation of Long House Valley in which each cell is allocated to one of 7 different zones. These differ in their agricultural yield (of maize) and are variably susceptible to changes in the Palmer Drought Severity index (a measure of the impact of moisture and temperature on

crop growth). Additionally, the model includes a raster map of water sources. In later versions of the model, variability in soil quality within zones is modelled stochastically by the simple expedient of adding a random number drawn from a uniform distribution between zero and some upper bound representing the spatial harvest variance.

Each agent represents a household of 5 persons. Agents farm one map cell and occupy a separate unfarmed residential location which must be within 1km of their farmland. Agents have a fission age, at which they spawn a new household, and an age of death, when they are removed from the model. In the first version of the model these attributes were the same for all agents, but in later versions some stochastic heterogeneity was introduced by randomly drawing these values from a uniform distribution with specified lower and upper bounds. The goal of agents is to grow sufficient maize to meet their annual requirement for survival. Agents who anticipate falling short search for a new cell to farm as per the rules in table 14.1 and, if successful, move there. Agents who exceed their fission age have a chance of spawning a new household, which take a fraction of the parent household's stored maize.

The model is run from A.D. 800–1350 in annual time steps. At each time step the Palmer Drought Severity Index is updated, which alters the yield of map cells. The map of water sources is also updated, which is one of the criteria used by agents attempting to move to a new cell to farm. Agents also pursue their goals (harvesting maize, possibly relocating and possibly fissioning) once per time step. The result of iterating these processes is a simulated annual record of population size and settlement location.

Further details of the model can be found in several sources. The version of the model distributed as part of the standard NetLogo model library includes an ODD-like description, which can also be viewed at <http://ccl.northwestern.edu/netlogo/models/ArtificialAnasazi>. More detail, including tables of agent attributes and rules in the original model are published in Axtell et al. 2002. Similar information is provided by Janssen 2009, who additionally also describes certain submodels (for example, how exactly the agricultural yield is calculated).

Experiments

The first version of the model has 17 parameters, and the model was initially run with values based on ethnographic accounts of historic Pueblo groups, as per table 14.2. It was found that with these “base case” (Axtell et al. 2002) parameter values the model could reproduce qualitative features of the history of demographic changes and settlement patterns in Long House Valley, but the actual population sizes were up to six times too large (Axtell et al. 2002, Kohler et al. 2005). Subsequent adjustment of farming yields to reflect characteristics of prehistoric maize coupled with the introduction of landscape and agent heterogeneity, as mentioned above, resulted in the model closely matching the historic population sizes (estimated from room counts).

The experimental design for the version of the model with greater stochasticity entailed calibrating the model by varying the upper and lower bounds of the stochastic parameters to find the values which produced the best fit between the simulated and historic population sizes (Axtell et al. 2002). This was

undertaken for both individual runs and for averages of 15 runs, the latter reflecting the fact that runs with identical parameters can produce different results by chance alone.

Janssen (2009) subsequently conducted a further round of experiments on a version of Long House Valley model re-implemented in NetLogo. He was able to replicate the results reported by Axtell et al. 2002, although it is interesting to see (Janssen 2009, fig. 3) that even the calibrated model can produce quite variable results, some of which do not so convincingly match the qualitative features of the population history (fig. 14.5). Perhaps more importantly, Janssen (2009, para. 4.1) also conducted experiments designed specifically to answer the question “What leads to the good fit of the simulation with the aggregated population data?”. He found that the fit between the simulated and historic population is primarily a function of landscape carrying capacity rather than parameters determining the longevity of households or at what age they might fission.

Implications

The best fitting runs of the calibrated model produce annual population sizes that track the estimated historic values uncannily well up until abandonment of Long House Valley. If Janssen’s analysis is correct, this may be primarily a function of the quality of the carrying capacity estimates derived from painstaking palaeoenvironmental research. On the other hand, even the best-fitting runs fail to predict the complete depopulation of Long House Valley at circa AD1300 and so all those who have analysed the model are in agreement that it has convincingly demonstrated that environmental factors alone can not account for the abrupt abandonment of the valley. Indeed, Kohler et al. 2005 suggest that archaeologists should instead look for sociopolitical or ideological drivers of this event. The role that ABM might play in this next instalment of research is discussed by Janssen.

Conclusion

Archaeological ABM are used for a variety of purposes and vary greatly in their complexity. Twenty—perhaps even ten—years ago, ABM was almost always computationally ‘cutting edge’ in some way, and this is still true of some more complex models, especially those requiring high performance computing and/or generating virtual reality visualisations. On the other hand, many recent archaeological ABMs have been implemented using well-established software and run on relatively mainstream hardware. This does not mean that those archaeological ABM’s are not computationally demanding, but that hardware and software are now sufficient to permit greater focus on other issues such as experimental design. The fact that the technological aspects of ABM have in many cases become less remarkable (literally so in recent publications) suggest that the technique has genuinely come of age as useful part of the archaeological toolkit. As the technology of ABM becomes ever more accessible it is hoped that this chapter will help users understand what makes an archaeological ABM scientifically productive.

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Tables

Table 14.1: Rules for choosing new farming and settlement locations (from Axtell et al. 2002, Table 2).

A. Identification of agricultural location:

The location must be currently unfarmed and uninhabited.

The location must have potential maize production sufficient for a minimum harvest of 160 kg per person per year. Future maize production is estimated from that of neighboring sites.

If multiple sites satisfy these criteria the location closest to the current residence is selected.

If no site meets the criteria the household leaves the valley.

B. Identification of a residential location:

i) The residence must be within 1 km of the agricultural plot.

ii) The residential location must be unfarmed (although it may be inhabited, i.e., multihousehold sites permitted).

iii) The residence must be in a less productive zone than the agricultural land identified in A.

If multiple sites satisfy these above criteria the location closest to the water resources is selected.

If no site meets these criteria they are relaxed in order of iii then i.

Table 14.2: Original ‘base’ parameter values for the Long House Valley model (from Axtell et al. 2002, Table 4).

Parameter	Value
Random seed	Varies
Year at model start	A.D. 800
Year at model termination	A.D. 1350
Nutritional need per individual	800 kg
Maximum length of grain storage	2 years
Harvest adjustment	1
Annual variance in harvest	0.1
Spatial variance in harvest	0.1
Household fission age	16 years
Household death age	30 years
Fertility (annual probability of fission)	0.125
Grain store given to new household	0.33
Maximum farm to residence distance	1,600 m
Initial corn stocks, minimum	2,000 kg
Initial corn stocks, maximum	2,400 kg
Initial household age, minimum	0 years
Initial household age, maximum	29 years

Figures

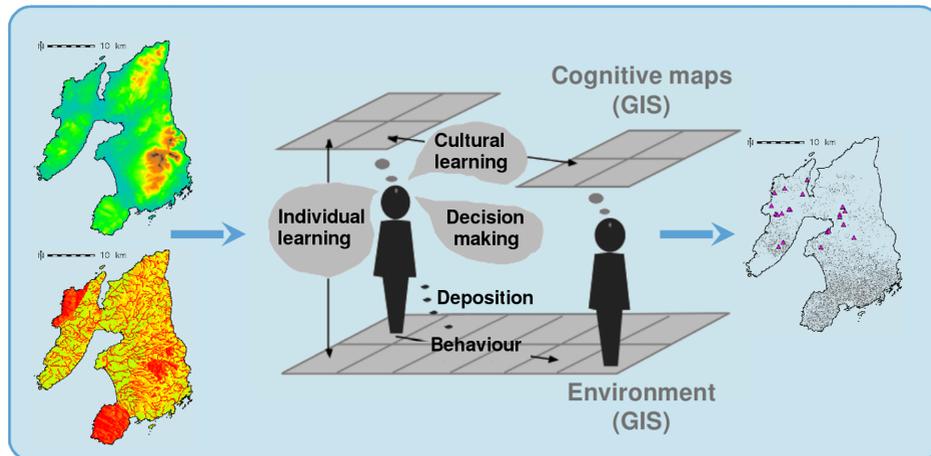


Figure 14.1: Schematic illustration of the features of an ABM with cognitive agents, based on the model described in M. W. Lake (2000) “MAGICAL Computer Simulation of Mesolithic Foraging”, in T. A. Kohler and G. J. Gumerman, Eds., *Dynamics in Human and Primate Societies: Agent-Based Modelling of Social and Spatial Processes*, New York: Oxford University Press, pp. 107–143. Mapping data ©Crown copyright and database rights 2019 Ordnance Survey (100025252).

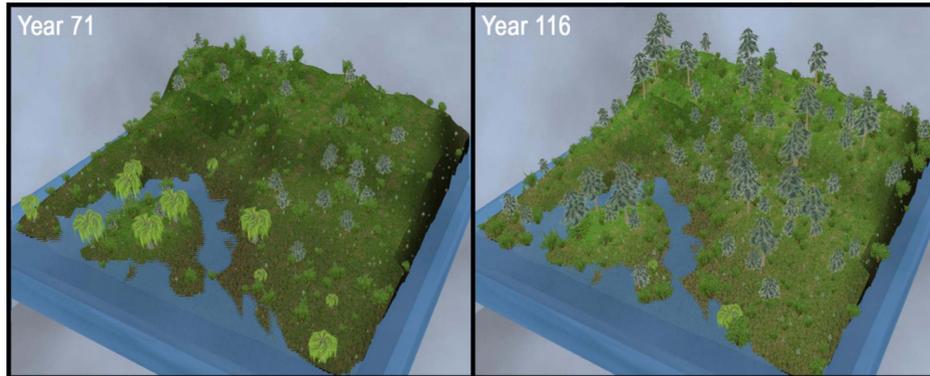


Figure 14.2: Example of the realistic rendering of a simulated landscape. Adapted with permission from E. Ch'ng and R. J. Stone (2006) "3D Archaeological Reconstruction and Visualisation: An Artificial Life Model for Determining Vegetation Dispersal Patterns in Ancient Landscapes", *Proceedings of the International Conference on Computer Graphics, Imaging and Visualisation (CGIV06)* 0-7695-2606-3/06

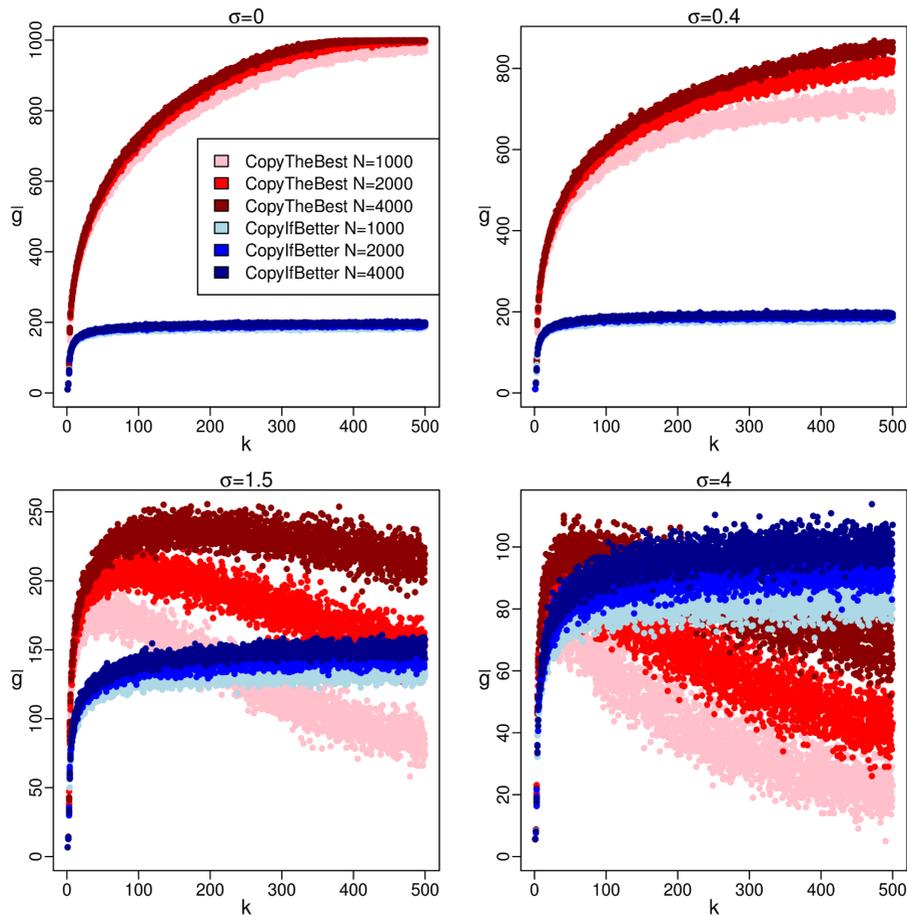


Figure 14.3: Graphed ABM simulation results which collectively illustrate several aspects of experimental design: (i) plotted points of the same colour and k value differ due to stochastic effects alone; (ii), two different parameters σ and k are varied; and (iii) two different agent rules, “CopyTheBest” and “CopyIfBetter” are explored. Reproduced with permission from figure 4 in E. R. Crema and M. W. Lake (2015) “Cultural Incubators and Spread of Innovation”, *Human Biology* 87: 151–168.

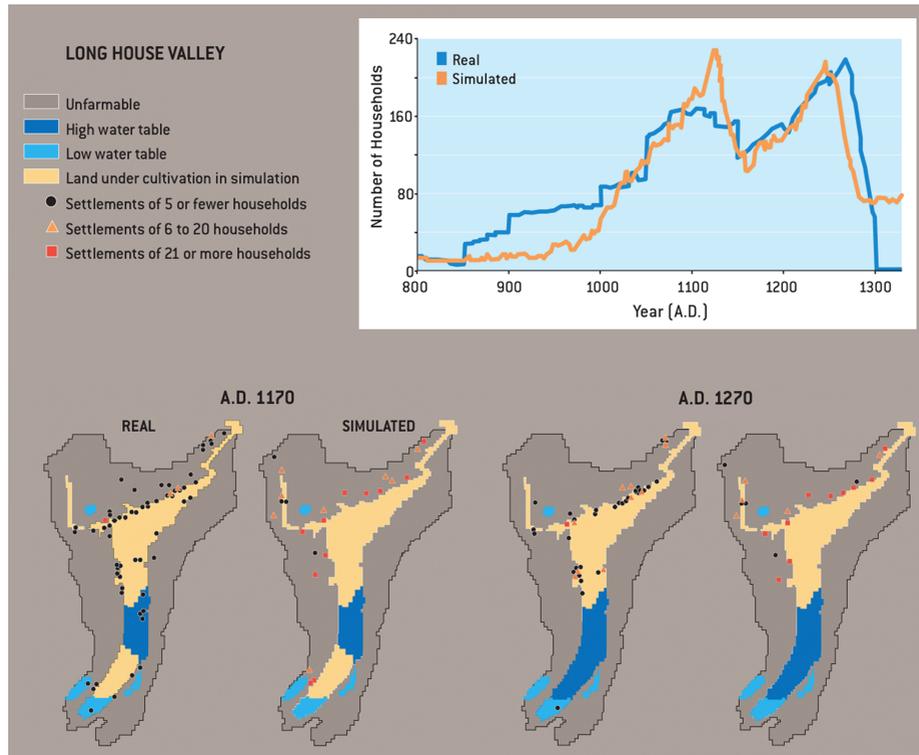


Figure 14.4: Comparison of Long House Valley simulation results with archaeological evidence. Adapted with permission from T. A. Kohler, G. J. Gumerman and R. G. Reynolds (2005) "Simulating Ancient Societies", *Scientific American* 293: 76–84.

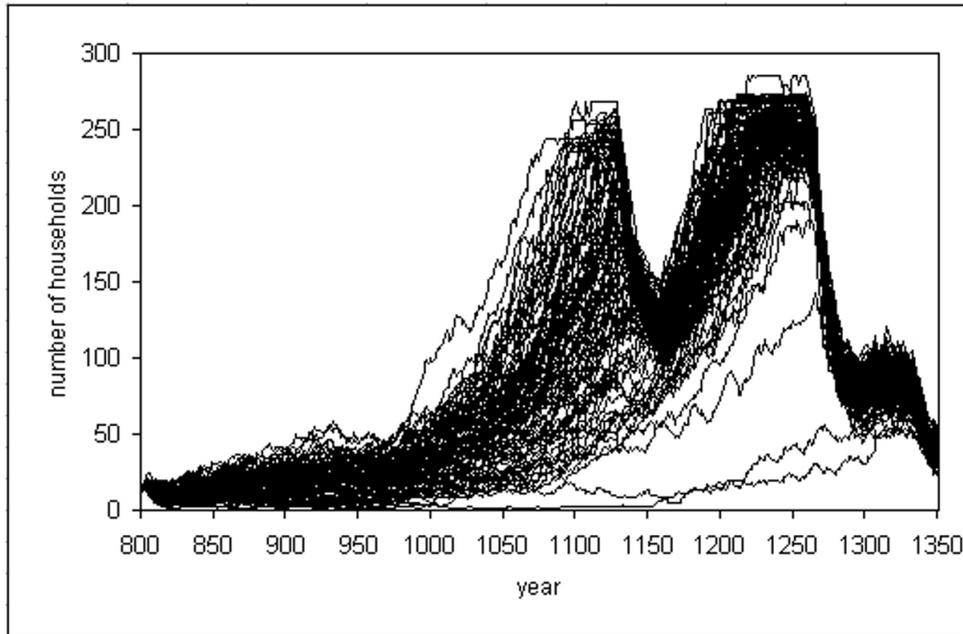


Figure 14.5: Population curves produced by 100 runs of the calibrated Long House Valley Model, differing only in random seed. Reproduced under a CC-BY-4.0 license from M. A. Janssen (2009) "Understanding Artificial Anasazi", *Journal of Artificial Societies and Social Simulation* 12 (4) 13 <http://jasss.soc.surrey.ac.uk/12/4/13.html>.