The use of pedestrian modelling in archaeology, with an example from the study of cultural learning

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Abstract. In this paper I briefly review the use of computer simulation in archaeology and argue that pedestrian modelling has the potential to overcome many of the problems associated with earlier simulation studies. I then introduce the MAGICAL simulation software, which was written to facilitate the use of multiagent simulation within a geographical information system. In the final part of the paper I describe the use of MAGICAL to study the evolution of cultural learning among early hominids.

1 Computer simulation in archaeology

Anthropologists (Hays, 1965) and archaeologists (Doran, 1970) were introduced to computer simulation in the late 1960s and early 1970s and have made sporadic use of the technique ever since. Although the first experiments were accompanied by great optimism (Whallon, 1972, page 39), most of them either were overly simplistic or required more input data than was available (Doran and Hodson, 1975), with the result that by 1981 the majority of archaeologists considered simulation "mildly interesting but on the whole not particularly useful" (Aldenderfer, 1981, page 12).

The first wave of North American simulations had been conducted as part of the new archaeology, a paradigm shift which reflected the impact of positivism on the social sciences during the 1950s and 1960s (Gibbon, 1989), but was particularly influenced by the new geography (Harvey, 1969) and von Bertalanffy's (1950) general systems theory. Consequently, the majority of early studies (for example, Levison et al, 1973; Thomas, 1972; Wobst, 1974) treated culture as a system for adapting to the environment. Later studies continued the emphasis on systems thinking, some claiming to test hypotheses (Gunn, 1979; O'Shea, 1978; Zubrow, 1975) and others (Black, 1978; Cooke and Renfrew, 1979; Zimmerman, 1977; Zubrow, 1981) claiming a heuristic function. In general, those that sought to test hypotheses rarely convinced, usually because they failed to make sufficiently detailed predictions about the archaeological record. On the other hand, heuristic models typically benefited only the developer, a problem which became increasingly acute as more archaeologists rejected the systems framework.

In contrast to the situation in North America, most of the modelling undertaken in the United Kingdom had been explicitly methodological and often *did* provide results that were of use to others. It is notable that Hodder was involved in many of these simulations, including modelling the nature of rank-size relationships in settlement growth (Hodder, 1979), the effect of trade mechanisms on artefact dispersal (Hodder and Orton, 1976), and a test for association between point distributions (Hodder and Okell, 1978). Indeed, it can be argued that Hodder's own move to structuralism (1982) and then poststructuralism (1986) goes some way to explaining why such studies ceased in the 1980s. In this case it was not that stimulation per se had been found wanting, but that the essentially functionalist framework within which it was used had been superseded by new theoretical concerns and, eventually, an antiscientific epistemology (Tilley, 1991).

Despite these setbacks, archaeologists have shown renewed interest in simulation during the 1990s. This has been fuelled by two developments in particular. First, some archaeologists have turned to evolutionary biology as a source of both method and theory. Simulation studies inspired by population biology have been used to address long-term or spatially extensive change (Steele et al, 1998; Zubrow, 1990). Conversely, studies inspired by behavioural ecology (Mithen, 1990) have focused on the decision-making and fitness of individual organisms, providing, it has been argued (Mithen, 1989), a more testable alternative to the recent concern with agency (Barrett, 1994). Second, the new science of complexity (Lewin, 1992) has enabled archaeologists to build formal models of aspects of human behaviour that had been neglected in the earlier generation of systems models. At the macro level the mathematics of catastrophe (Zeeman, 1977) and chaos (Thompson and Stewart, 1986) have provided a means of studying the often endogenous origins and inherent unpredictability of, for example, the prestige goods economy (McGlade, 1997) and the rise of urbanism (van der Leeuw and McGlade, 1997). At the micro level, agent-based modelling (DeAngelis and Gross, 1992; Gilbert and Troitzsch, 1999) has enabled archaeologists to build more sophisticated models of hunter–gatherer decisionmaking, either to predict aggregate patterns in the archaeological record (Mithen, 1990), or to investigate the origins of increased social complexity (Dean et al, 2000; Doran et al, 1994; Kohler et al, 2000). Together, these new techniques provide more appropriate tools in a changed intellectual climate which emphasises endogenous change and the role of the individual in creating, sustaining, and dissolving larger scale regularities (Epstein and Axtell, 1996; Gilbert, 1995; Reynolds, 1987; Holland and Miller, 1991).

Given this history, archaeology is now ready for the introduction of pedestrian models. Although many of the simulations conducted in the 1970s and 1980s were strongly spatial, the nonlinear dynamical and agent-based models which have replaced them have mostly been aspatial. In the case of nonlinear models, the sophisticated treatment of causality has been won at the expense of explicit spatial reference. The first agent-based models also neglected space. For example, in Mithen's (1990) model of Mesolithic hunting, hunters learn the probability of encountering prey at a given point in time, but not at any specific location. Similarly, although Lake (1995) modelled patch choice, the spatial relationship of the patches was not modelled. More recent agent-based models have included space as a 'container' for individuals, but not as a element of their knowledge. For example, Kohler et al's (2000) model of population aggregation and abandonment does not explicitly model the settlers' knowledge of their environment as distinct from the environment itself. One notable exception is the Evolution of Organised Society (EOS) project (Doran, 1989; 1997; Doran and Palmer, 1995; Doran et al, 1994) in which agents, representing Palaeolithic hunter–gatherers, form alliances in order to procure resources on a landscape. In this case, the agents build models of both the landscape and other agents.

The virtue of pedestrian modelling is that it offers a formal method compatible with current interests in endogenous change, individual fitness, and human agency, but which can also be used to relate these to the spatial component of archaeological data. The possibility of modelling spatial decisionmaking is clearly of considerable significance for a discipline whose remit include hunter–gatherer foraging strategies, colonisation, settlement location, and the 'choreography' of ritual.

2 The MAGICAL software
The MAGICAL (Multi-Agent Geographically Informed Computer AnaLysis) software provides a multiagent modelling extension to the Geographical Resources Analysis Support System (GRASS) geographical information systems (GIS) package.

By combining support for agent modelling with the spatial database facilities of GIS it allows pedestrian modelling of hunter – gatherer subsistence strategies. The MAGICAL software was written by me for a research project directed by Steven Mithen at the University of Reading, UK (Lake and Mithen, 1998; Lake, 2000).

Although developed in the context of a specific field project (Mithen, forthcoming), it was always intended that the MAGICAL software should have a wider application within archaeology and related disciplines. To that end it offers a compromise between flexibility and the need for specialist computing skills. A system of activity and rule tokens allow an archaeologist who is not a computer programmer to build a simulation model customised to his or her needs, provided that it falls within the basic paradigm described below. In this way it differs from the EOS project, which allowed the simulation of more complex forms of cooperation between agents, but did not provide any facility for customisation by an end user with a different problem. Likewise, it differs from the Santa Fe Institute's SWARM toolkit (Minar et al, 1996; and see Schelhorn et al, 1999, for an example of a pedestrian model implemented using SWARM) which offers more flexibility, but ony if the end user is able to program in a high-level computer language—a skill which few archaeologists possess.

2.1 The modelling paradigm
The MAGICAL software was conceived to further the long-standing use of simulation for the study of hunter – gatherer activities (Mithen, 1994). Consequently, its capabilities reflect a research tradition that has generally emphasised mobility, subsistence, and more recently 'rational' decisionmaking (Bettinger, 1991; Mithen, 1990). For example, having 'rationally' calculated the benefit of moving to a particular location in the landscape, agents may then expend energy moving there before regaining it if they successfully encounter a resource. The MAGICAL software builds on earlier studies of such behaviour by providing a framework for modelling the acquisition and use of spatial knowledge. Individual learning, cultural learning, and decisionmaking can all be applied to spatially referenced data and/or agents' knowledge of that data, as appropriate. The MAGICAL software implements spatially referenced knowledge through its close integration with GIS. Specifically, it allows each agent to maintain its own cognitive maps in the form of GIS raster maps. Admittedly, it appears that the Cartesian model of geographic space implied by an x – y referenced GIS raster map is probably very different (Mark and Frank, 1990) from the cognitive maps (Kuipers, 1983; Lloyd, 1989; Tolman, 1948) used by humans to store spatial information. Nevertheless, since chimpanzees are able to calculate transport costs as a function of both weight and Euclidean distance (Boesch and Boesch, 1984), there can be little doubt that even untrained humans are able to think using at least some aspects of the metric implied by Cartesian raster mapping. In other words, MAGICAL raster cognitive maps store relevant information even if they do not accurately model the underlying psychology.

2.2 The software design
The MAGICAL software can be decomposed into three main elements: the collection of agents, the event scheduler, and the spatial database.

The central tenet of agent-based modelling is that each agent has its own set of internal state variables affected by its own history. This principle is often extended so that each agent's behaviour is governed by its own set of principles, and it may also be the case that each occupies a discrete spatial location in the environment. The MAGICAL software implements agents as entities that have a range of properties and possible behaviours (or actions) which are appropriate for modelling human behaviour according to the paradigm outlined above. They also possess a unique identifier and spatial location. The properties currently implemented include energy level, rate of energetic

return on foraging, and group membership; the actions include random and directed movement, search, and the exchange of information with other agents. Three important actions recently added to the software are birth, reproduction, and death. These and other examples are illustrated in the simulation which is described later in this paper.

The MAGICAL software offers nonprogrammers flexibility for research within the behavioural-ecology paradigm because the agent's behavioural principles are not coded into the software, but are instead provided at run-time in the form of a user-specified 'genotype'. A given genotype may be shared among all agents or it may be unique to just one. A genotype comprises a set of action and decision tokens that specify how an agent's properties are updated and how they influence subsequent decisionmaking. The example in table 1 is best conceived as a table with one row for each possible (current) action. The content of a given row specifies the conditions under which one or more actions follow the current action. The conditions are (reverse-Polish) logical expressions which refer to one or more of the agent's properties, the contents of the data maps, or the agent's knowledge of the data maps. If a condition evaluates true then the agent undertakes the associated activity.

The MAGICAL software implements the passage of time by allowing agents to add events to a queue managed by a scheduler. Events are simply requests to perform a particular action at a specified time in the future. The processing of events is continuous throughout the simulation and takes place as follows. An agent, having decided how and when to act next, adds the appropriate event to the queue. Meanwhile, following each increment of the simulation clock, the scheduler traverses the queue and removes all those events whose time stamps are less than or equal to the current time. On removing each event the scheduler instructs the appropriate agent that it may now perform the requested action. When that action is complete the agent decides what to do next and adds a new event to the queue. This process continues until the total simulated time has elapsed.

Table 1. Cultural learning genotype.

begin	[crdnhb: al][rs: al][rd: al][shbp: al][jg: al][rab: al];
mtd	[waita: stgz][die: stgz not][rad: stgz not][atr: al][dvh: stgz];
mdhb	[id: al];
is	[mbchbfd 0: at dhgeeb or sd not and][sdtt: sd not at not and dhgeeb not and] [mdhb: sd][rcb: sd];
rgxid	[crdnhb: dd not][crod: dd];
sixig	[aga: al];
waita	[waitc: at][waitd: at not];
id	[rgxid: al][rs: al][ifc: al];
ee	[mtd: al];
crod	[ptb: al];
waitb	[die: al][rad: al];
waitc	[hvfd 0: dhgz][rvhn 0: dhgz not];
waitd	[hvfd 0: dhgz dhgeeb and][rvhn 0: dhgz not dhgeeb not or];
sdtt	[ee 0: al];
hvfd	[rvhn 0: al];
rvhn	[is: al];
atrep	[waitb: al];
ptb	[atrep: aartb][ptb: aartb not];
crdhb	[sdtt: al];
crdnhb	[sdtt: al];
mbchbfd	[sdtt: ergeone at not and][mbhb: ergeone not at or];
mbhb	[sdtt: at not][crdhb: at].

The MAGICAL software achieves the spatial referencing of agent activities and knowledge by means of close integration with the GRASS GIS package. Indeed, the software is made available to the end user as a set of three GRASS commands. The simulation program can access a GRASS database which may contain one or more of three types of spatial data. The first, which is mandatory, is information about the agents' environment. This is stored in as many raster map layers as necessary. Contrary to earlier documentation (Lake and Mithen, 1998), it is now possible for agents to alter this environment by, for example, harvesting and thereby depleting resources. The second type of data is the agents' own knowledge about their environment. As noted above, this is stored in the form of cognitive (raster) maps. Each agent has as many cognitive maps as there are environment map layers. The third type of data records the spatial location of agent activities during the simulation. It is possible, for example, to produce a raster map recording the frequency with which agents visited each map cell, or the number of archaeological artefacts they deposited in each cell.

The benefit for pedestrian modelling of integrating simulation with GIS is that it allows both input and output (spatial) data to be manipulated using any of the available GIS tools. Although there is at least one other example of such integration (Westervelt and Hopkins, 1999), the MAGICAL software is unique in using the GIS data structures to model both the agents' environment and their knowledge of it. The virtue of this approach is that it allows both the simulated environment and the agents' knowledge to be analysed using the same tools.

3 The evolution of cultural learning
This part of the paper describes the use of the MAGICAL software to investigate a research problem in early hominid archaeology. Since that research is still in its infancy the results reported here are not conclusive, but they do serve to demonstrate the relevance of pedestrian modelling for a growing area of archaeological research.

3.1 The research problem
It is often claimed that humans are unique among animals because we are cultural. Although this is partly the result of the increased 'intelligence' that comes with our exceptionally large brain size (relative to body size) there is another important factor: our greatly enhanced ability to learn from one another. Without such learning, culture would be much less complex since there would be no 'ratchet effect' whereby modifications to cultural traits accumulate over time (Tomasello et al, 1993, page 495). For this reason, archaeologists and anthropologists are keen to understand the origin of the so-called 'cultural learning' ability that is required to support the ratchet effect (Tomasello et al, 1993).

There is insufficient space here to review the psychology of cultural learning. The following discussion simply summarises the position, argued at length in Lake (1995), that underpins the pedestrian model described below. From an evolutionary perspective the key question is what is the minimum requirement for cultural learning? There is much debate about whether imitation is the simplest form of cultural learning (for example, Boyd and Richerson, 1985; Heyes, 1993; Heyes and Plotkin, 1989; Hull, 1982; Rogers, 1988; Tomasello et al, 1993; Whiten and Ham, 1992), but I accept Heyes's (1993) argument that imitation (as defined by any of these authors) is not a form of cultural learning because it does not adequately prevent or discourage the novice from modifying information learned from the model. The problem is that excessive modification of information learned from others causes a high enough frequency of reinvention that it prevents the ratchet effect. Heyes thinks that such modification can be prevented only

by additional psychological processes that allow individuals "to hold and transmit information about temporally and spatially remote objects and events or metaphysical entities", "to adhere to social norms or hold moral beliefs", and "to store information extra-somatically" (page 1006).

Heyes's position receives support from cognitive ethnology and evolutionary epistemology. The ethological evidence suggests that although chimpanzees can imitate (Hayes and Hayes, 1952; Tomasello et al, 1993; Whiten, 1993; Whiten and Ham, 1992), so-called chimpanzee 'culture' (McGrew, 1985; 1992; McGrew and Tutin, 1978) does not exhibit the ratchet effect (Heyes, 1993; Tomasello et al, 1993). Consequently, it would appear that imitation is not sufficient to effect cultural learning. Following a different line of reasoning, evolutionary epistemologists (Odling-Smee, 1983; Plotkin, 1994) argue that the adaptive function of cultural learning is to track environmental change over a range of frequencies which, in the main, fall between those to which biological evolution and individual learning are most sensitive. In other words, cultural learning makes it possible to learn about changes that are too rapid or localised to elicit a coherent genetic response, but too slow or distant to be apprehended by individual learning. If Plotkin and Odling-Smee are correct, then the very function of cultural learning is to allow individuals to hold and transmit information about temporally and spatially remote objects and events.

I have suggested elsewhere (Lake, 1995) that this function might have become particularly important around 2 million years ago. By that time our ancestors (early members of *Homo*) and other early hominid species (such as the robust australopithecines) were no longer tree dwellers, but largely terrestrial (Vrba, 1985). Habitation on the highly seasonal savanna required novel foraging adaptations. It appears that the robust australopithecines and the early members of *Homo* represent a divergence in strategies to cope in the dry season, with the former opting for a low-quality diet and the latter a high-quality diet (Foley, 1987; Vrba, 1985). The enlarged teeth of the robust australopithecines (Jolly, 1970) coupled with patterns of tooth microwear (Grine, 1981; Walker, 1981) support the idea that they spent long periods of time feeding on hard objects, probably grass seeds and the coarse dry fruits found in savanna environments (Kay, 1985). In contrast, early members of *Homo* do not possess the dental specialisation of the australopithecines and are associated with archaeological evidence for opportunistic meat eating (Potts, 1988), suggesting the expansion of the diet to include meat. It is possible that this type of cultural learning evolved in early *Homo* because the distribution of meat-bearing carcasses was subject to a degree of spatial and temporal variation which was particularly difficult to track by individual learning alone.

3.2 The model

The pedestrian model described in this section represents a first step towards testing whether the spatial variability in carcass availability would have favoured the evolution of cultural learning. It is not a realistic model of foraging by early *Homo*, but was constructed to ascertain which measures of spatial variability capture those aspects of resource distribution that influence the selective benefit of cultural learning. A more realistic model will be constructed only if it can be demonstrated that resource distribution does indeed influence the selective benefit of cultural learning, and if suitable measures of spatial variability can be identified. To date, the model captures three aspects of foraging: an environment comprising a spatial distribution of resources, explicit decisionmaking, and learning about the distribution of resources.

This first model was designed to establish whether fractal dimension measures an aspect of resource distribution capable of influencing the selective benefit of cultural

learning. Fractal dimension was chosen for this initial study for two reasons. First, it is possible to compute theoretical surfaces of a given fractal dimension D. A method using spectral synthesis (Saupe, 1988) has been implemented for the GRASS GIS (Wood, 1994). Consequently, by modelling the environment as a surface, such that the z value at each (x, y) coordinate represents the energetic return available from harvesting resources at that location, it is a simple matter to generate a series of raster maps representing different resource distributions each of a known fractal dimension, D. For our purposes, increasing values of D from $D > 2$ to $D < 3$ can be taken to imply increasing spatial variability in the value of z. The second virtue is that it should be possible to measure the fractal dimension of resource distribution in the modern analogs of past environments. In this way, the spatial structure of the theoretical environments can be compared with the conditions similar to those that actually prevailed.

Agent decisionmaking is explicitly modelled as part of the process of foraging. Agents must sustain themselves by searching for and harvesting resources in their environment. The rules used by animals to make decisions about where to forage and what to harvest have been extensively studied by behavioural ecologists (Stephens and Krebs, 1986) and form the core of optimal foraging theory (OFT). According to OFT animals should attempt to maximise their long-term energy gain (Stephens and Krebs, 1986) so as to increase their reproductive success. Although it is doubtful whether humans attain the optimal rate of energy gain (Martin, 1983), they do, nevertheless, succeed in improving their foraging efficiencies, or 'meliorising' (Dawkins, 1982). It is most likely that this is achieved through the use of rules of thumb rather than by complex calculation (Mithen, 1990). Since this is even more likely to have been true of early *Homo*, all agents were given the simple rule that they should move to and harvest from the neighbouring map cell that offers the greatest net energetic return given the cost of travel to and from each candidate map cell.

The model includes agent decisionmaking primarily as a means of ensuring that the quality of an agent's knowledge will affect its fitness. Since agents make decisions according to the content of their cognitive maps, it follows that those with more extensive or recent knowledge will typically achieve higher energetic returns and eventually greater reproductive success. All agents begin life ignorant of their environment and then learn about it as the simulation proceeds. The mechanism by which a given agent learns is determined by its genotype. Those with the 'individual learning' genotype learn solely from their own experience. When such an agent visits a map cell the net energetic return available at that location is copied to the agent's cognitive map. If the agent harvests the cell, its cognitive map is updated accordingly. Once the agent has left the cell it will remain ignorant of any subsequent changes in the return available at that location until it revisits the cell. Agents with the 'cultural learning' genotype also learn from their own experience, but in addition they are able to learn from one other. At the end of the day they share whatever information they gleaned in the course of that day's foraging by pooling their knowledge in a group cognitive map which is then used to update their own cognitive maps.

The selective benefit of cultural learning is determined by allowing the population of agents to breed according to their fitness. Breeding takes place at the end of each generation by a process of *tournament selection* (Gilbert and Troitzsch, 1999, page 225). Each agent randomly picks a partner and whichever has the achieved the highest energetic return then produces two offspring. Offspring always inherit their parent's genotype. In this way, cultural learning will spread through the population if it enhances the relative fitness of those agents who engage in it.

As explained above, the rules governing agent behaviour in a MAGICAL simulation are specified in the agent genotypes. The 'cultural learning' genotype used in this

model is reproduced in table 1. The activity sequence for a cultural learner is illustrated as a flowchart in figure 1. Activities in part 'S' are performed many times during each simulated day, those in part 'D' are performed only at the end of each day, and those in part 'G' are performed only at the beginning and end of each simulated generation. The individual activities are:

G1 The agent is born with a copy of its parent's genotype and initial properties, or if this is the first generation, with the genotype and properties specified in an initialisation file.

S1 The newly born agent randomly chooses a target cell to which it intends to travel (crdnhb). That cell must be within the travel radius specified as one of the agent's properties. The agent then sets the target as its immediate destination (sdtt).

S3 The agent moves to its immediate destination (mtd) and expends energy (ee) doing so. The amount of energy expended per cell traversed is specified as one of the agent's properties.

S4 If the agent's energy level is no longer greater than zero (stgz) then it dies.

S5 If the net energetic return available at the agent's new location is not greater than zero (dhgz) then it makes no attempt to harvest the resource. If the energetic
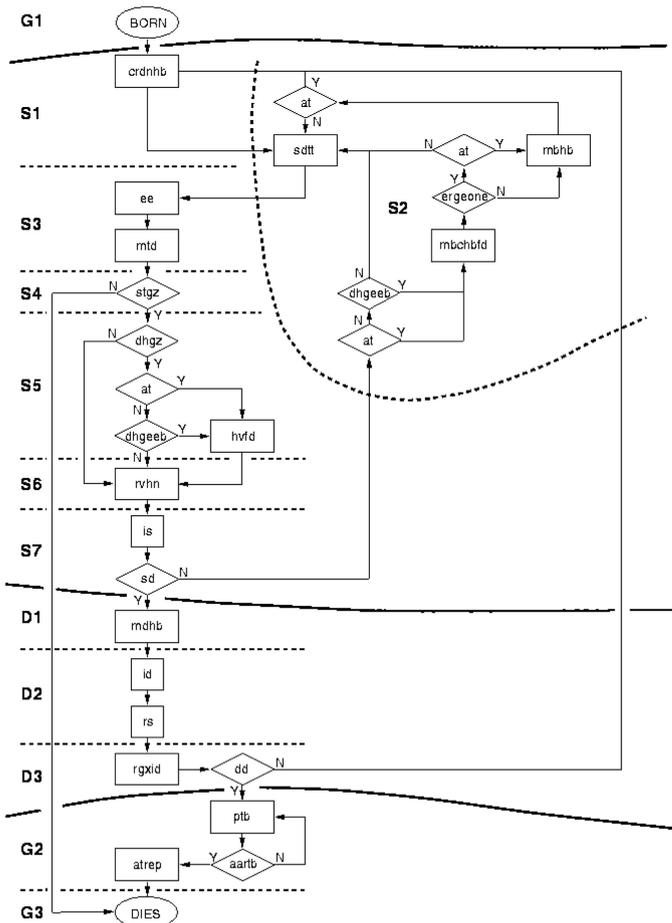
Figure 1. Flowchart of cultural learning genotype.

return is greater than zero then it harvests the resource if the new location is also the target cell (at), or the energetic return is equal to or greater than that expected at the target cell (dhgeeb).

S6 The agent always learns by observing the resources available in all cells within the learning radius specified as one of its properties (rvhn). This effects individual learning about the environment.

S7 The agent increments its step counter (is) It decides what to do next according to whether or not it has reached the end of a day (sd).

S2 If the agent has not reached the end of a day it chooses a new destination according to the contents of its cognitive map. If it had not reached its chosen target cell, and the energetic return at the new (now current) location is less than that expected at the target cell, then it sets its immediate destination to whichever cell within the allowable travel radius is nearest the target. Alternatively, the agent chooses a new target. It initially chooses the cell that offers the highest rate of energetic return (including the cost of travel to it and back to the central place) among those that are still accessible within the number of steps remaining (mbchbfd). It makes this cell the target, so long as the expected rate of return is greater than or equal to one (ergeone)—that is, the benefit exceeds the cost. If not, then the agent attempts to reduce its losses by targeting the cell that offers the best net energetic return en route back to the central place (mbhb). Either way, the agent usually then sets its immediate destination to whichever cell within the allowable travel radius is nearest the new target. The only exception occurs when the cell with the best net energetic return en route back to the central place is actually the current location. In this case the agent attempts to avoid eventual death by 'risking' a visit to a randomly chosen cell within the allowable travel radius (crdnhb).

D1 If the agent has reached the end of a day it will normally have returned to the central place, but if not it does so now (mdhb).

D2 The agent increments its day counter (id) and resets the step counter (rs).

D3 The agent asks all other agents in the group to share whatever information they gleaned in the course of the day's foraging (rgxid). As a result it eventually exchanges information with other cultural learners, but not individual learners. This process of cultural learning about spatially remote resources is coordinated by means of a group genotype not shown in figure 1. Once information exchange is complete, the agent decides what to do next according to whether or not it has reached the end of a generation (dd).

S1 If the agent has not reached the end of its maximum lifespan (the generation interval) it randomly chooses a target cell to which it intends to travel (crdnhb).

G2 If the agent has reached the end of its lifespan then it prepares to breed (ptb) by waiting until all other agents in its generation are also ready to breed. Once this condition is met (aartb) it breeds by pairwise tournament selection (atrep), as described earlier.

G3 The agent finally dies.

3.3 Experiments

To date, 1000 simulations have been run, divided between three theoretical environments. Figure 2 (see over) shows the three environments, characterised by fractal dimensions (a) 2.1, (b) 2.5, and (c) 2.99. Each is a raster map created using the GRASS

(a)

(b)

(c)
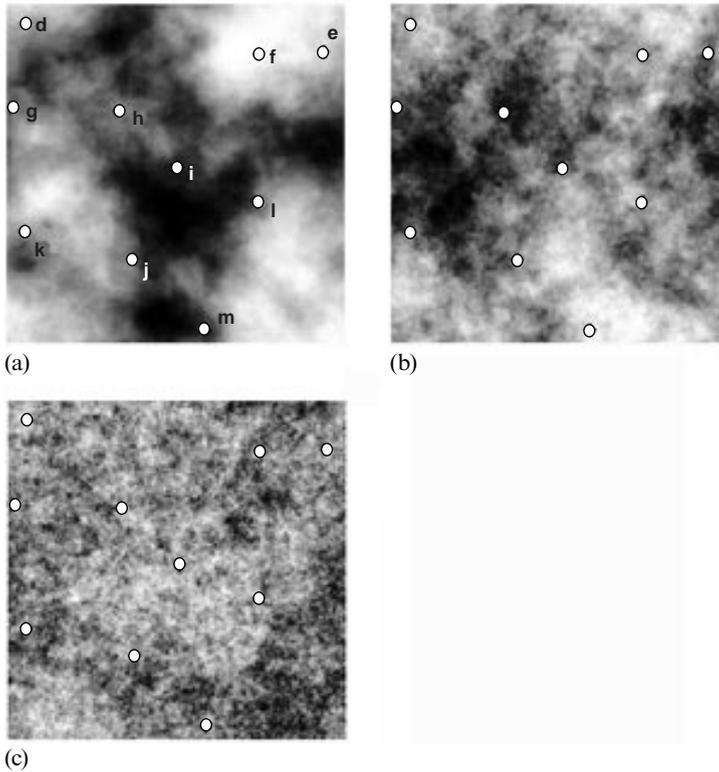
Figure 2. Environments with fractal dimension (a) 2.1, (b) 2.5, and (c) 2.99.

function r.surf.fractal and then scaled so that all cell values fall in the range $+100$ (white) to -100 (black), inclusive. Recall that these values represent the net energetic return from harvesting resources in each cell.

Three identical sets of three experiments (a, b, and c) were conducted: one set per environment. One additional experiment (d) was carried out for the environment with fractal dimension 2.1. The individual experiments will be referred to as a2.1, a2.5, a2.99, b2.1, ..., c2.99, d2.1. All ten experiments involved an initial population of three cultural learning agents and three noncultural learning agents. As a result, the model ignores the possibility that cultural learning might be able to evolve only when it is present at some threshold frequency. Note, however, that any requirement for a minimum frequency is likely to be an artefact of the simplifying assumption of discrete traits (Wilson and Dugatkin, 1997). In all cases the population was allowed to evolve for

Table 2. Simulation parameters common to all experiments.

Parameter	Value
Initial energy level of agents	1000.0
Energetic cost of traversing one map cell	2.0
Assumed energetic return from unknown map cells	-200
Maximum number of map cells to move per time step	2
Number of steps per day	200
Number of days per generation	4
Total number of time steps per simulation	10 000

thirteen generations. Agents were always initialised with the properties listed in table 2. The experiments within each set differed only in respect of agent harvesting behaviour. In type-a experiments, agents harvested 100% of the resource available in a given cell, whereas in type-b experiments they harvested 20%, in type-c experiments 10%, and in the type-d experiment only 5%.

Each of the ten experiments required 100 simulations to control for occasional randomness during decisionmaking and also for the arbitrary choice of central place. Ten simulations were made for each of ten randomly chosen central places. The latter are marked in figure 2, from which it can be seen that they cover a wide range of 'local' environments. Each of the ten simulations per central place were started with a different seed for the random number generator.

Figures 3 and 4 (see over) provide a snapshot of agent behaviour during a typical simulation. Figure 3(a) illustrates the paths of three cultural learning agents during the first simulated day. Each has explored a different area: one to the upper right, one to the upper left, and one to the lower left. The initial lack of consensus is expected because the agents had not yet shared their initially limited knowledge. Figures 4(a) – 4(c) illustrate the three agents' cognitive maps and confirm that they did, indeed, possess very different knowledge prior to sharing information by cultural learning. Figure 4(d) illustrates one of the agent's cognitive maps immediately after sharing information by cultural learning. As a result of this information exchange all three

(a)   (b)
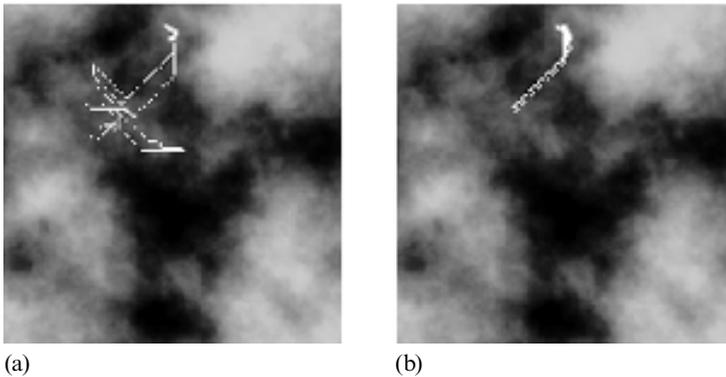
Figure 3. Traces of three sharing agents over (a) the first day and (b) the second day.

agents explored the same area during the second day; this is illustrated in figure 3(b).

Figures 5 and 6 (see over) illustrate population evolution in a single simulation run as part of a type-a experiment on the environment with fractal dimension 2.1. Figure 5 records the actual numbers of agents and figure 6 records the corresponding relative frequency of cultural learners in the population. Note that total population sizes typically either remain fairly stable or dwindle towards extinction. The latter occurs when the central place is located in a particularly resource-poor part of the environment. The infrequent occurrence of population growth is a result of the breeding method, since on average half of the agents have two offspring and the other half have none. Figure 7 (see over) records the changing relative frequency of cultural learners in all 100 runs of experiment a2.1.

The results of all ten experiments are recorded in table 3 (see over). In all cases the relative frequency of cultural learners in the population is the mean result from 100 simulations, as described above. Note also that it refers to the average relative frequency at the end of thirteen generations, or immediately prior to extinction in cases where the population became extinct before the simulation ceased. It is apparent from table 3 that
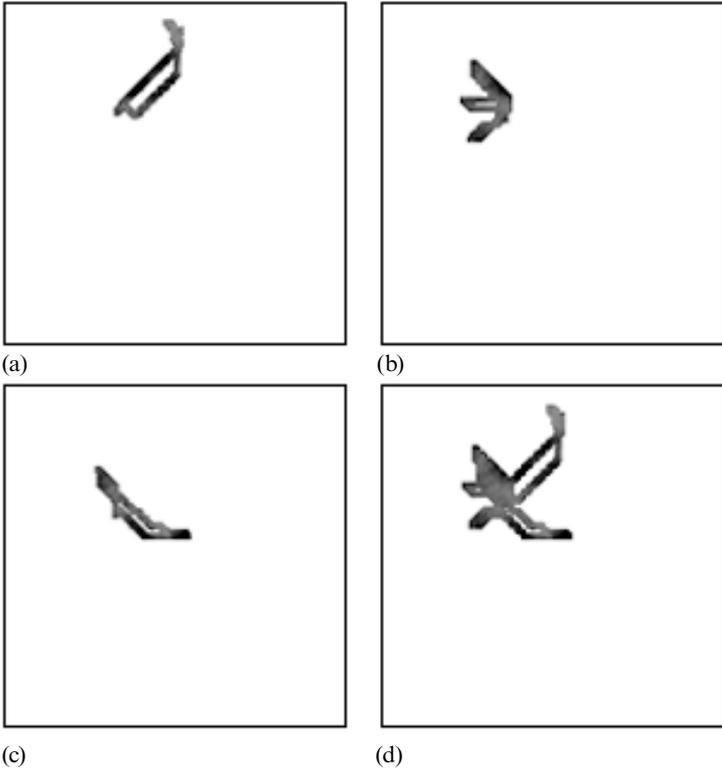
Figure 4. Cognitive map of (a) agent 1, (b) agent 2, and (c) agent 3 before cultural learning, and of (d) agent 3 after cultural learning.
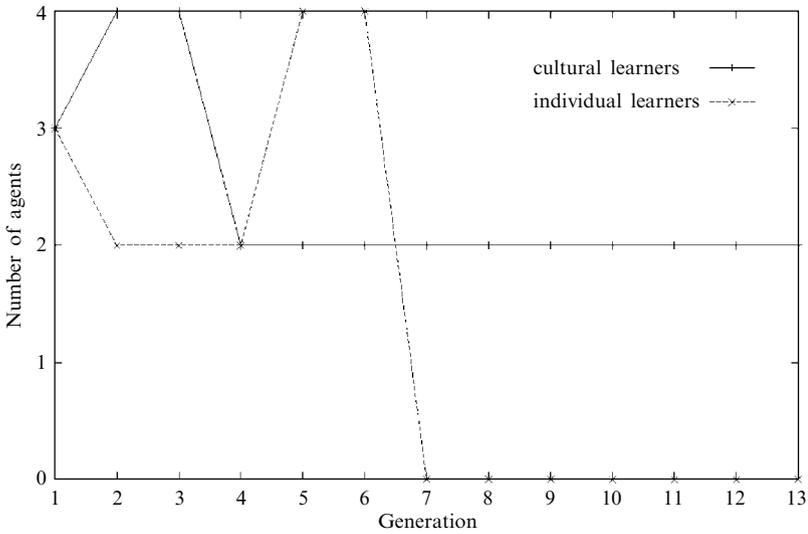
Figure 5. Actual numbers of agents in population (1 run).
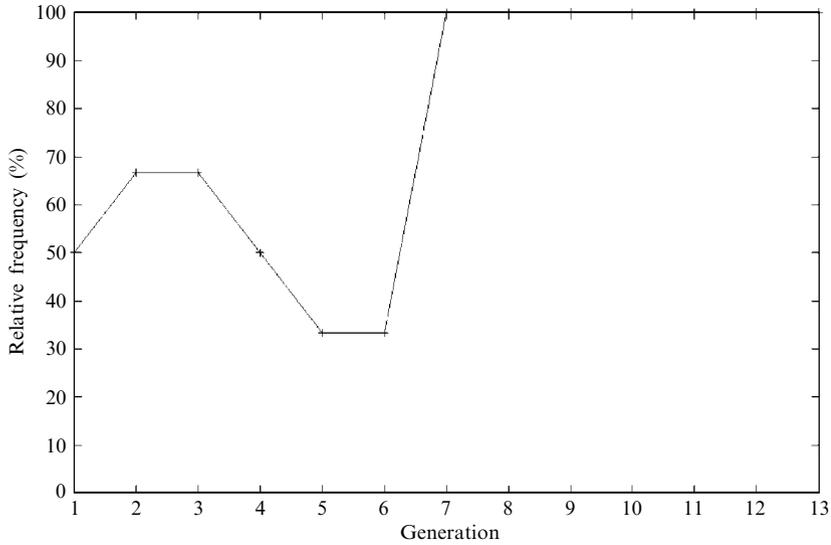
Figure 6. Relative frequency of cultural learners in the population (1 run).
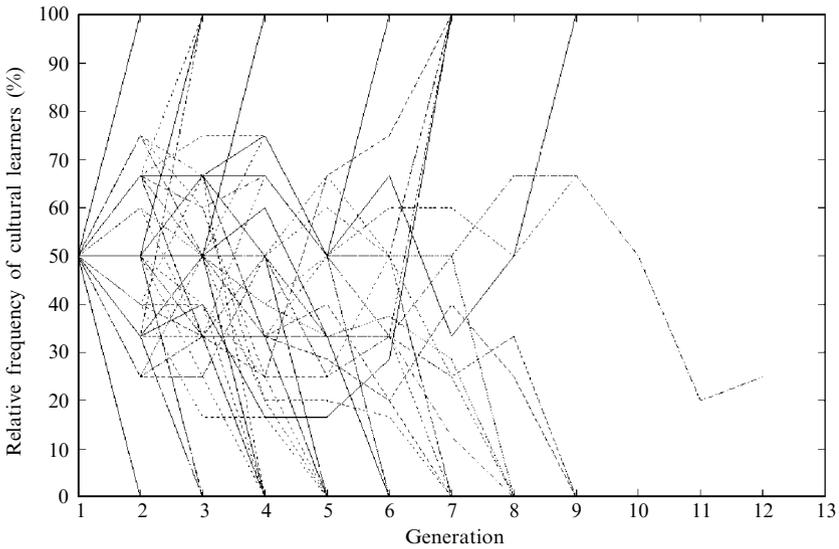
Figure 7. Relative frequency of cultural learners in the population (100 runs).

Table 3. Mean relative frequency of cultural learners after 13 generations, or immediately prior to population extinction.

Fractal dimension	Experiment type			
	a	b	c	d
2.1	0.369	0.280	0.280	0.300
2.5	0.300	0.230	0.210	na
2.99	0.244	0.193	0.134	na

na, not applicable.

reducing resource variability (in other words, decreasing fractal dimension, D) increases the selective benefit of cultural learning, as witnessed by the increasing frequency of cultural learners within the population. Nevertheless, since the relative frequency of cultural learners is always less than 0.5, it appears that pure individual learning is always the better strategy irrespective of resource variability. This is misleading to the extent that it is only true on average.

Table 4 records, for each experiment, the percentage of simulations in which the population fixed on one type of learning (in other words, the relative frequency of one type was equal to one), and the percentage of those cases in which the population fixed on cultural learning. It can be seen that in the majority of simulations the population fixed on one or the other learning strategy, probably because they are not strictly alternate strategies. In every experiment the population most frequently fixed on individual learning alone, but in one case (type a experiment in environment with $D = 2.1$) some 35.3% of simulations that went to fixation actually fixed on cultural learning. More significantly, it is clear from table 4 that the percentage of fixations on cultural learning is inversely correlated with the fractal dimension of the environment, irrespective of experiment type. Consequently, although none of the three environments probabilistically favours cultural learning over individual learning, reduced variability does nevertheless increase the selective benefit of cultural learning. Thus, the results from these initial ten experiments support the general thrust of Plotkin and Odling-Smee's argument about the function of cultural learning, but do not identify a general class of environments in which cultural learning would be expected to evolve more often than not.

It is worth considering why the experiments have so far failed to identify a class of environments that probabilistically favour cultural learning. One obvious possibility is that cultural learning—as modelled here—results in competition for the same resources, thereby cancelling out the benefit of locating superior resources. This needs further

Table 4. Percentage of simulations that went to fixation (%FX) and percentage of fixations that favoured cultural learning (%CL).

Fractal dimension	Experiment type							
	a		b		c		d	
	%FX	%CL	%FX	%CL	%FX	%CL	%FX	C%L
2.1	98	35.3	100	28.0	100	28.0	100	30.0
2.5	98	28.4	100	23.0	100	21.0	na	na
2.99	92	18.4	95	16.2	96	10.7	na	na

na, not applicable.

Table 5. Number of simulations that favoured cultural learning as a percentage of those that went to fixation, arranged by central places d–m in environment $D = 2.1$.

Experiment type	Central place									
	d	e	f	g	h	i	j	k	l	m
a	50.0	50.0	40.0	20.0	50.0	50.0	33.3	33.3	30.0	10.0
b	20.0	60.0	10.0	20.0	50.0	20.0	30.0	20.0	20.0	30.0
c	60.0	0.0	30.0	10.0	70.0	30.0	20.0	50.0	0.0	10.0

na, not applicable.

investigation, although it is striking (table 4) that cultural learning was more strongly favoured when competition was greater (in other words, when individuals harvested 100% of the resource in a given cell). Another possibility is that fractal dimension does not measure the most relevant aspects of resource distribution. As already noted, populations did sometimes fix on cultural learning, and table 5 shows that this was more likely to occur for some choices of central place than for others (indeed, at some, cultural learning actually evolved more often than not). For that reason it was decided to investigate whether the frequency with which the population fixed on cultural learning correlates with the resource availability at specific search distances from the central place, on the assumption that cultural learning might confer greater selective benefits when good resources are located further from the central place. Figure 8 illustrates the average net energetic return available from cells within 0–100.0, 100.0–141.4, 141.4–173.2, and 173.2–200.0 steps of each of the ten central places, d–m, in the environment with $D = 2.1$. These radii were chosen to provide bands of equal area (sample size) in order to allow meaningful comparison of the variances. It is clear from figure 8 that, in general, neither the mean resource availability, nor the variance in resource availability are a function of search radius in this environment. It follows that the central places where populations were more likely to fix on cultural learning were not necessarily those that were located further from good resources. The specific aspect of resource availability that probabilistically favours cultural learning over individual learning remains to be identified.
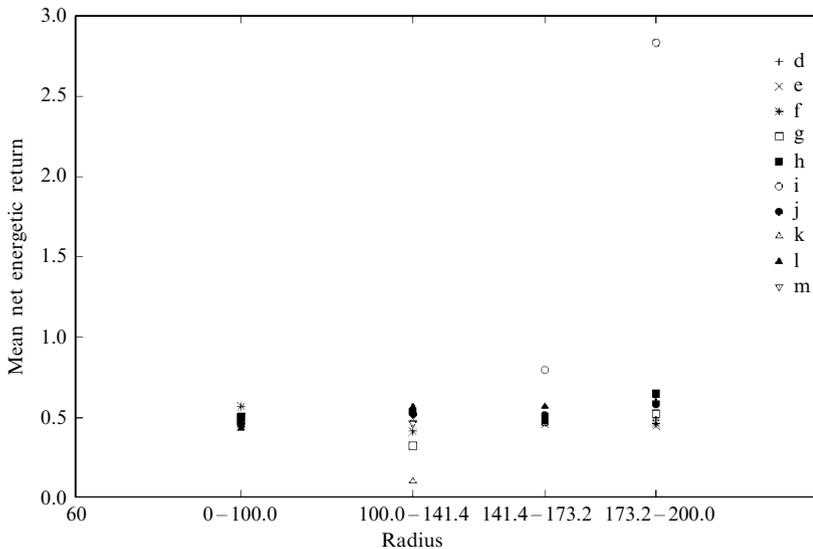
Figure 8. Resource availability by search radius for environment $D = 2.1$.

4 Concluding comments

In this paper I have argued that pedestrian modelling has the potential to overcome some of the criticisms levelled at earlier archaeological uses of simulation. In particular, it provides a means of exploring current interests in individual fitness and agency, in contexts where the spatial knowledge of past people is central to our understanding of their behaviour. The MAGICAL software was developed to ease the process of implementing pedestrian models for a class of archaeological problems that typically focus on mobility, subsistence, and 'rational' decisionmaking. With additional programming it may be extensible to other research areas such as the 'choreography' of ritual.

The integration of the MAGICAL software within a GIS package is particularly convenient for those conducting spatial analysis.

The close coupling between simulation and GIS was clearly illustrated in the example application presented in section 3. This was a pedestrian model designed as a first step towards testing the hypothesis that the need to locate high-quality foodstuffs in savanna environments may have provided a strong selective pressure favouring the evolution of enhanced cultural learning among early *Homo*. Its function was to help discover what aspects of spatial structure potentially influence the selective benefit conferred by cultural learning. The experiments conducted to date suggest that fractal dimension (of a surface) measures a property of resource distribution that is, indeed, correlated with the selective benefit of cultural learning. Nevertheless, the results also suggest that other aspects of spatial structure are also—possibly more—important in determining the probability that cultural learning will evolve. Future research will continue the use of pedestrian modelling in an attempt to elucidate what these might be.

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