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Mind, the gap in landscape-evolution modelling

John Wainwright[1]* and James D.A. Millington[2]
[1] Sheffield Centre for International Drylands Research, Department of Geography, University of Sheffield, Sheffield, UK
[2] Center for Systems Integration and Sustainability, Michigan State University, East Lansing, MI, USA

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*Correspondence to: John Wainwright, Sheffield Centre for International Drylands Research, Department of Geography, University of Sheffield, Winter Street, Sheffield, S10 2TN, UK. E-mail: J.Wainwright@sheffield.ac.uk

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Earth Surface Processes and Landforms

ABSTRACT: Despite an increasing recognition that human activity is currently the dominant force modifying landscapes, and that this activity has been increasing through the Holocene, there has been little integrative work to evaluate human interactions with geomorphic processes. We argue that agent-based models (ABMs) are a useful tool for overcoming the limitations of existing, highly empirical approaches. In particular, they allow the integration of decision-making into process-based models and provide a heuristic way of evaluating the compatibility of knowledge gained from a wide range of sources, both within and outwith the discipline of geomorphology. The application of ABMs to geomorphology is demonstrated from two different perspectives. The SPASIMv1 (Special Protection Area SIMulator version 1) model is used to evaluate the potential impacts of land-use change – particularly in relation to wildfire and subsequent soil conditions, runoff and erosion – over a decadal timescale from the present day to the mid-twenty-first century. It focuses on the representation of farmers with traditional versus commercial perspectives in central Spain, and highlights the importance of land-tenure structure and historical contingencies of individuals' decision-making. CybErosion, however, considers changes in erosion and deposition over the scale of at least centuries. It represents both wild and domesticated animals and humans as model agents, and investigates the interactions of them in the context of early agriculturalists in southern France in a prehistoric context. We evaluate the advantages and disadvantages of the ABM approach, and consider some of the major challenges. These challenges include potential process-scale mismatches, differences in perspective between investigators from different disciplines, and issues regarding model evaluation, analysis and interpretation. If the challenges can be overcome, this fully integrated approach will provide geomorphology a means to conceptualize soundly the study of human–landscape interactions by bridging the gap between social and physical approaches. Copyright © 2010 John Wiley & Sons, Ltd.

KEYWORDS: agent-based models; land-use change; multidisciplinary; simulation; heuristic modelling; policy-related models; human impacts

Introduction

There has been increasing recognition over the past decade of the importance of human activity in modifying landscapes at the global scale, whether by agriculture or by more direct earth-moving operations (e.g. Hooke, 2000; Wilkinson, 2005; Wilkinson and McElroy, 2007; Montgomery, 2007). Although the absolute rates of these modifications are likely to be overestimated (Parsons *et al.*, 2004; Parsons *et al.*, 2006a, 2006b; Wainwright *et al.*, 2003), it is clear that human activity has long been an important factor in changing rates of geomorphic processes, both by direct impacts on land cover (e.g. Wainwright and Thornes, 2003) and by indirect feedbacks such as by modifications to the climate (e.g. Ruddiman, 2003). Furthermore, at the global scale, the rate of human modification of process rates has been interpreted as increasing exponentially (Hooke, 2000; Wilkinson, 2005) in parallel with rapidly increasing populations. This interpretation is certainly oversimplistic (e.g. McNeill, 1991; Wainwright and Thornes, 2003) and thus methods need to be developed to evaluate and understand the linkage more clearly. The critical point is that geomorphic process rates in general are more sensitive to human action that they are to climatic variability (Wainwright, 2008).

Gregory (2000) highlighted the general lack of work by geomorphologists on human impacts until (with notable exceptions) the 1970s. Although this work expanded, especially within an applied geomorphology perspective from the 1980s onwards, there are two principal problems with the approaches taken. First, the methodology has largely been one of producing case studies, without consideration of how these separate case studies might build into a coherent body of understanding. One reason for the case-study-centred approach to the influence of human activity on the landscape has been the small spatial scale of studies that has been an inevitable consequence of the process-based approach to geomorphology (e.g. Wainwright *et al.*, 2000). However, a number of methodological developments have led to the (re-) evolution of a number of larger scale perspectives to the discipline (e.g. Bishop, 2007; Summerfield, 2005). There is therefore a need to address the ways in which human activity can be integrated with the renewed interest in landscape-scale approaches. Secondly, the approach of applied geomorphology has largely been one of environmental management and integration into engineering views of the landscape (e.g. Fookes *et al.*, 2003) with commensurate problems (e.g. Bracken and Wainwright, 2006). Gregory's call for a 'cultural physical geography' has received little attention in a way that would address these issues.

At the same time, there has been a significant body of work on the effects of decision-making on land-use change (e.g. Lambin, 2003; Lambin *et al.*, 2003). Little of the work on land-use and land-cover change (LUCC) and the consequences of LUCC, has specifically focused on processes of runoff production, erosion and resulting patterns of landscape evolution, although again with some notable exceptions (e.g. Schoorl and Veldkamp, 2001; Bithell and Brasington, 2009; Buis, 2008). Furthermore, given the themes of the IGBP-IHDP Global Land Project are 'Dynamics of Land Systems', 'Consequences of Land System Change' and 'Integrating Analysis and Modelling for Land Sustainability' (GLP, 2005), it should be clear that geomorphology as a discipline has a significant part to play in an integrated Earth-system Science framework (Wainwright, 2009) if these separate strands can be combined coherently. We suggest that geomorphology is most likely to succeed in this and other challenges in producing a cultural physical geography if it can utilize and integrate concepts and approaches from other disciplines that consider land system dynamics, especially those that consider human activity. Thus, from this standpoint, the aim of this paper is to evaluate the role of work on decision-making and LUCC and its applicability with respect to understanding and modelling landscape evolution, with a specific focus on agent-based models (ABMs).

Understanding Decision-making and its Impact on the Landscape

If human activity is a significant control on landscape evolution, then evaluating the conscious and unconscious actions that lead to different activities is a critical step in a complete geomorphological methodology. The decisions that cause these different activities to occur at different times and in different combinations produce complex outcomes and thus landscapes that are typified by complex response and path dependency or contingency. Traditional geomorphological methodologies have struggled to extract meaning from geomorphic data in these contexts, not least because of problems of equifinality. Another reason for the lack of work in modelling decision-making has been the perceived complexity of the problem and the lack of a cross-over from disciplines where such work has occurred for the last 50 years (see Wainwright and Mulligan, 2003). Paradoxically, the potential strength of a geographically based geomorphology has provided something of a negative heuristic in the development of an integrated approach to studies of decision-making in a geomorphological context, given the social and cultural geographies that have developed in the anglophone world (but cf. Parker *et al.*, 2003). Here, the development of theory and practice in modelling decision-making is reviewed in order to demonstrate that the basis for an integrated approach exists outside the present discipline.

Modelling from the top-down versus from the bottom-up

Past attempts to model landscape change as a result of human activity have taken a diverse range of approaches and methodologies that can be classified in many different ways (Parker *et al.*, 2003; Verburg *et al.*, 2006). However, one clear methodological distinction arises from two opposing modelling perspectives: on the one hand, an approach that addresses broad-scale, regional patterns of change resulting from the unknown decisions of actors within the region of interest; and on the other hand, an approach that considers the decision-making process of individual actors (Kellerman, 1989). The former approach assumes that general models of landscape change can be developed 'from the top-down' according to knowledge about the state, and changes in that state, of an entire region. The latter perspective considers it necessary to represent individual decision-makers' actions 'from the bottom-up' because global patterns emerge from their interactions.

The top-down and bottom-up perspectives result in different concepts of systems and the methods used to examine them [cf. the 'dynamic' and 'organizational' approaches, respectively, defined in the individual-based model (IBM) literature in ecology by Villa (1992)]. The top-down view conceives system dynamics as the result of variability in the components of an unchanging system structure. Equation-based models, systems approaches and statistical techniques are used to model changes in aggregated system state variables, usually at a single, fixed, level. In contrast, the bottom-up view emphasizes organizational change and structural complexity [or aggregated complexity as Manson (2001) has termed it]. From this view, understanding complex systems demands the consideration of the (changing) relationships of components, emphasizes the importance of the history of these relationships for future change, and expects the emergence of system properties that cannot be explained by decomposing the system into its component parts. In these circumstances, top-down, system-level equations of system dynamics and behaviour are unlikely to be achievable, especially when simulating social entities. A bottom-up approach provides the opportunity to use knowledge of lower-level system components to identify structures that are necessary or contingent (i.e. neither necessary nor impossible) for the observed system-level dynamics. Furthermore, the bottom-up approach allows the representation of the interaction of heterogeneous system components, and does not presuppose uniform or homogenous system components and interactions as the top-down approach often requires. These characteristics mean that bottom-up approaches are predominantly simulation-based (representing the behaviour and interactions of discrete, and potentially heterogeneous, entities) rather than analytically based as many previous top-down approaches have been (even if they are subsequently developed numerically).

Discrete-element, IBMs and ABMs exemplify the bottom-up approach. These modelling frameworks are increasingly recognized as a means to work across scientific disciplines to examine Earth systems and aid their management (Bithell *et al.*, 2008; Bousquet and Le Page, 2004). The naming conventions between these approaches highlight the differences between the characteristics of disciplines utilizing them and the systems they study. Discrete-element models are used to represent physical systems such as avalanches and débris-flow events (with a high number of interacting elements), IBMs to represent ecological systems such as forest communities (with fewer interacting organisms), and ABMs to represent social systems such as urban populations (with interacting individuals that possess agency). Here, we focus on the use of ABMs to represent human decision-making.

In the social sciences, formal models of human decision-making and behaviour have predominantly been developed by economists. Such models have conventionally been based on the (fictional) perfectly economically rational human *Homo economicus*, who acts to optimize their wealth above all else (Janssen and Jager, 2000). However, Simon (1957) recognized that rarely do actors in the real world optimize their behaviour, and instead merely try to do 'well enough' to satisfy their goal(s). Simon (1957) termed this non-optimal, cost-benefit assessment, behaviour 'satisficing', and laid the basis for much of the theory of bounded rationality since. In situations where information, memory or computing resources are not complete (as is often the case in the real world) the principle of bounded rationality is possibly a more pertinent approach (Goodrich *et al.*, 2000). Furthermore, goals of satisficing (or optimized behaviour) need not be economic and might also include social justice (*Homo politicus* – Nyborg, 2000) or environmental sustainability (*Homo sustinens* – Siebenhuner, 2000). An agent-based approach provides a means to represent these imperfect, heterogeneous actors in a way that traditional, analytical methods cannot; as agents who determine their interactions on the basis of internal social norms, behavioural rules and data acquired from their own individual experiences and histories (Tesfatsion, 2002). A variety of interacting social norms and behaviours (e.g. predatory, cooperative, error-prone, destructive, altruistic, imitative) can be simulated to 'grow' economies and societies *in silico* for analysis in real-time (Epstein and Axtell, 1996).

Generally, agent-based modelling approaches are composed of a (virtual) environment in which agents are linked via relationships that allow them to perform operations to perceive, produce, transform and manipulate objects according to set rules (Ferber, 1999) (Figure 1). Agents that adapt their behaviour according to experience are also possible via evolutionary computation methods such as genetic programming, which allows agents to evaluate and select solutions from a suite of options through time (Edmonds, 1999). In landscape models, a cellular model is most frequently used to represent the agents' environment. Interdependencies and feedbacks are specified between agents and their environment to produce an integrated landscape model (Parker *et al.*, 2003, Matthews *et al.*, 2007). Agents in these models may represent organizational structures including individual humans or animals, collections of individuals (e.g. households or herds) and other social, political or economics institutions and entities. By explicitly representing actor behaviour, bottom-up ABMs are inherently more process-based and deductive when compared with top-down statistical and mathematical models which take an inductive approach to fit parameters and curves to empirical observations (e.g. Brown *et al.*, 2004), often undermining the process basis of a model (Wainwright *et al.*, 2009). However, if ABMs are to be developed to improve our understanding or to support analysis of potential future landscape states (e.g. scenario and policy analysis), credible representations of the agents must be produced (Robinson *et al.*, 2007). When developing rules of relationships and response, three key issues must be addressed (Bousquet and Le Page, 2004):

(1) Decision-making: what mechanisms do agents use to make decisions? How are agents' perceptions, actions and responses linked?
(2) Control: how are agents related and synchronized?
(3) Communication: what information may be passed from on agent to another? How is it passed?

Empirical approaches for informing the production of credible agent behaviours and interactions include sample surveys and interviews with the actors being represented, participant observation, and field and laboratory experiments (Robinson *et al.*, 2007). Participatory modelling approaches involve stakeholders throughout the modelling process, often allowing those actors who are being represented in an ABM to communicate with modellers and contribute to the development of agent behaviours by participating in role-playing games (e.g. Castella *et al.*, 2005) or by interacting with simulation agents themselves (e.g. Nguyen-Duc and Drogoul, 2007). In past settings, these credible agent behaviours must also be developed with reference to ethnographic and anthropological sources and evaluated against patterns in the archaeological record.

Dynamic agent-environment interactions

As important as determining appropriate rules for agent interaction and behaviour are, the potential strength of this class of models is the dynamic linkage between human activity and environmental response. Parker *et al.* (2008a) describe three approaches for linking human-environment models. A fully integrated model will represent the dynamic interactions and key feedbacks between coupled human and natural systems across both space and time. This integrated approach can thus represent the reciprocal impacts of human activity on natural

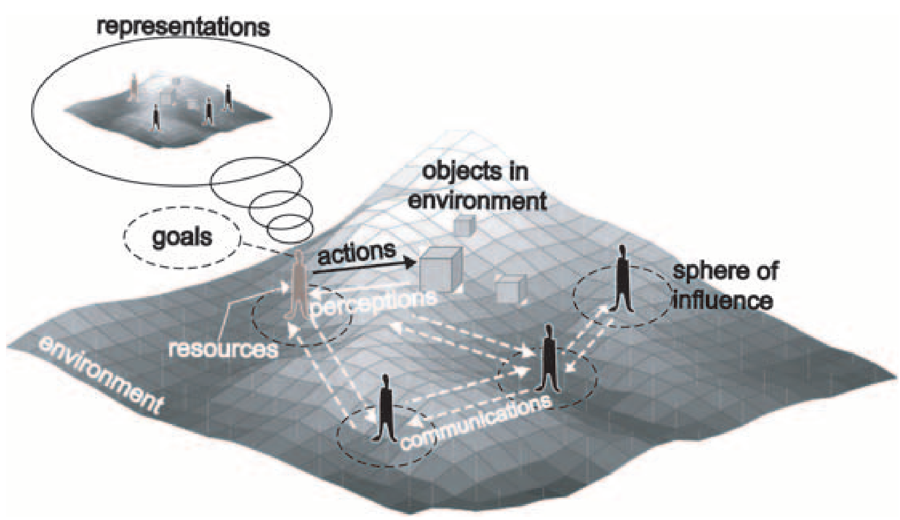

Figure 1. Structure of a multi-agent system with agents interacting with each other and their environment (after Ferber, 1999; Wooldridge, 2002; Bousquet and Le Page, 2004).

systems and differs from models that use single linkages (a social science model as input to a natural science system or *vice versa*), or multiple unidirectional linkages (e.g. a natural–social–natural linkage in a one-way chain). Specifically, multiple unidirectional models illustrate a trajectory of consequential change, and do not link directly back to the original system. Wainwright (2008) highlights the problem that these 'scenario' approaches provide static representations of complex interrelationships with the danger, in the worst case, of leading to the simulation of totally unrealistic conditions (e.g. the continuation of farming once the total soil thickness has been lost from an area).

Good examples of agent-based models that have achieved reciprocal linkages between humans and their environment, overcoming the dangers highlighted by Wainwright (2008), are Manson (2005) and An *et al.* (2005). Manson (2005) places emphasis on environmental interactions with actors in his actor-institution-environment modelling framework to consider the southern Yucatán Peninsula of Mexico. The model considers soil fertility, elevation, slope, aspect and precipitation as factors influencing land-use decisions. Specifically, soil fertility is modelled as being dependent upon the type of and duration of land use and therefore subject to actors' decisions. Reciprocally, these decisions are assumed to be dependent upon soil fertility. Manson (2005) also demonstrates another potential of ABM approaches to LUCC by considering the interaction of agents at two organizational levels – smallholder households and institutions (administration units, financial markets and conservation organizations). An *et al.* (2005) also consider human-environment interactions more explicitly than many models by tracking the life-histories of individual actors in their model to explore the impacts of household dynamics on panda habitat in China. The interaction between forest growth and harvest is represented in a spatially explicit manner based upon household locations and sizes. The authors found several non-linear and counterintuitive landscape responses to the conservation scenarios considered with potential policy implications.

These examples highlight several of the benefits of the agent-based approach and demonstrate the strides that have been made in integrating human activity into models of environmental change. Decision-making agents may take the form of several different organizational entities, and path dependencies within the system are represented. Furthermore, with appropriate structures, reciprocal feedbacks between physical environment and human activity are made explicit. Such a 'generative' approach to representing the influence of human decisions on the earth system allows the development and encoding of potential explanations of landscape-evolution that combine multiple scales, provides opportunities to identify and structure needs for empirical investigation, and brings the possibility of highlighting when prediction may not be a reasonable goal (Brown *et al.*, 2006, Epstein, 2007).

ABMs therefore allow the investigation of human–landscape interactions and dynamics and thus potentially overcome the problems noted in the introduction. Geomorphological applications of the approach are used in the next section to demonstrate how this might be done practically. Alongside their benefits, such applications also raise a number of challenges however. These challenges are addressed in the discussion.

Case Studies

Two case studies are presented here that allow the evaluation of different approaches of modelling decision-making at different spatial and temporal scales. In the first, modern and future (to 2026) land-use changes are simulated for an area of *c.* 830 km^2, with decision-making aggregated at the level of the household and larger socio-economic institutions. The second example models prehistoric decision-making at an individual level over periods of several centuries for an area of *c.* 120 km^2.

Special Protection Area SIMulator version 1 (SPASIMv1)

The Special Protection Area SIMulator version 1 (SPASIMv1) is an integrated socio-ecological landscape-simulation model, developed to examine relationships between changing human land use and the frequency and location of fires in a landscape typical of the Mediterranean Basin. Various scenarios are used to evaluate the impacts of exogenous social and economic decisions resulting from potential political policies over the next few decades. Given that fire régimes may modify surface runoff and associated sediment transport by enhancing or reducing soil hydrophobicity (Doerr *et al.*, 2000; Bowman and Boggs 2006), this model has potential to examine the consequences of changes in human activity on linked ecological, hydrological and geomorphological systems at the landscape scale. The model was developed using data for Special Protection Area number 56 (SPA 56) '*Encinares del río Alberche y Cofio*' in the autonomous community of Madrid, central Spain. SPA 56 is an area of *c.* 830 km^2 that contains a fragmented mosaic of multiple land uses and covers including pine and oak woodlands, monoculture farmland, multifunctional farmland, urban and recreational areas, and increasing extents of abandoned farmland. Further details about SPA 56 and recent LUCC in the area can be found in Romero-Calcerrada and Perry (2004) and Millington *et al.* (2007). SPASIMv1 is composed of a Landscape Fire Succession Model (LFSM – described in more detail by Millington *et al.*, 2009), and an ABM of agricultural land-use decision-making (described in more detail by Millington *et al.*, 2008) (Figure 2).

LFSMs are spatially explicit models that simulate the dynamic interaction of fire, vegetation, and often climate (Keane *et al.*, 2004). The LFSM developed for SPASIMv1 uses a state-and-transition approach to represent dynamics of several broad land-cover classes on a grid (of 30 m × 30 m pixels). These land-cover classes represent two dominant vegetation types with distinct life history traits and reproductive strategies (pine and oak), three mixed vegetation types (transition forest, deciduous and shrubland), two agricultural land-use classes (crops and pasture), and two non-vegetation land covers (water/quarry and burnt land). The vegetation classes are based on plant-functional types to account for the importance of key environmental resource constraints (water and light availability) and disturbance (fire and agriculture). The availability of solar radiation for vegetation growth is modelled as a function of the aspect of a pixel. Soil moisture and surface runoff are calculated using the Soil Conservation Service (SCS) curve number method (SCS, 1985). Surface runoff is routed spatially through the landscape as a function of topography (Jenson and Domingue, 1988). SPASIMv1 considers the impacts of varying intensities and frequencies of disturbance by representing two succession pathways ('secondary' or 'regeneration') between vegetation classes. Locations of seed sources are tracked to represent spatially variable seed availability and dispersal.

The representation of wildfire disturbance is separated into ignition and spread stages. Ignition frequency is controlled in

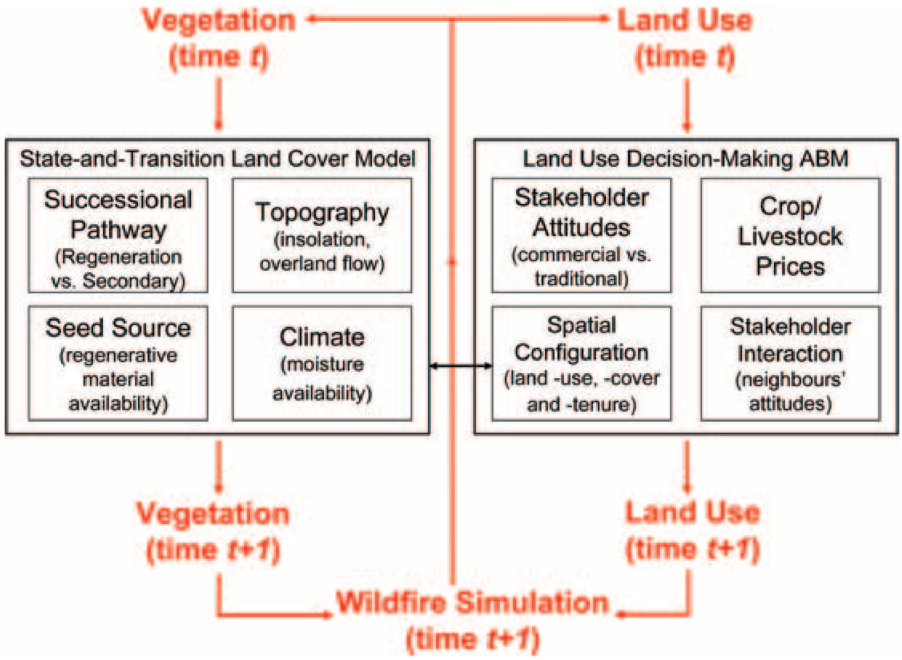

Figure 2. Flowchart showing the basic structure of SPASIMv1 and interactions of model components.

the model by climatic and anthropic factors, allowing it to represent the influence of changing climate, human population demographics and land use on wildfire ignition. Wildfire ignition location can be represented in the model as a random process, as the result of lightning strike or as the result of accidental human ignition. Lightning fires are assumed only to occur above an elevation of 1000 m in mountainous areas (Vazquez and Moreno, 1998). Locations of human ignition are modelled by considering the distance to recreational areas (e.g. picnic site), roads, tracks and recently burnt areas. These ignition mechanisms are not explicitly linked to the ABM (described later) but are influenced by land-cover composition and configuration which are a consequence of agents' actions. Intentional burning for agricultural purposes and arson is frequent in the Iberian Peninsula but is not currently represented in the model. The former may be added to the ABM model in future versions but the latter may be difficult to represent from an agent perspective given the paucity of data available (identifying individual arsonists has been found to be difficult and few arrests have been made by the Spanish authorities – Seijo, 2005). Wildfire spread is modelled using a cellular automata approach (see Millington *et al.*, 2006). Once a fire has been ignited in a given pixel it may then spread into any of the neighbouring eight pixels. In SPASIMv1, fire is assumed to completely burn all vegetation in a pixel, but future revisions to the model will include representation of variation in fire intensity. The probability of spread between pixels is modelled as a function of the flammability of each land-cover class (including biomass amount), slope (wildfire preferentially spreads upslope), local climate conditions (controlling fuel-moisture content), wind direction and strength, and the presence of wildfire mitigation efforts (e.g. fire breaks).

The ABM represents agricultural land-use decision-making of individual small-scale farmers, albeit aggregated at the level of the household. The model classifies land-use decision-making agents into two differing perspectives; 'commercial' agents who are perfectly economically rational, and 'traditional' agents who represent part-time farmers or those who manage their land because of its cultural, rather than economic, value. Agents may switch between these types depending upon individual agent profitability, landscape-wide profitability and agent age. These two agent types use different approaches to decide whether a pixel will be in one of three possible land uses: crops (vineyards, orchards), pasture (goats and sheep) or non-agricultural land. Pixels with orthogonal neighbours either in the same land state or owned by the same agent are considered to be individual fields. The status of each agent (age, wealth, perspective, pixels owned) is monitored at each time-step.

Commercial agents' land-use decisions are based on several factors related to profitability: market conditions, land-tenure fragmentation, transport costs and land productivity. At each time-step, commercial agents estimate profit in the next time step – if the land-use configuration of the land they currently own can be modified to improve profit, land-use conversions are made. Commercial agents may also buy and convert neighbouring abandoned pixels if it is likely to increase profit. Alternatively, if costs outweigh the value gained from a pixel in a specific land use, the pixel will be abandoned to become non-agricultural. Non-agricultural pixels rapidly transition to shrubland in the vegetation state-and-transition model of the LFSM. Traditional agents follow similar rules to commercial agents but (i) do not consider any profit-making activities, and (ii) do not seek to buy land from neighbours. Interviews with local stakeholders highlighted the importance many locals hold of continuing traditional agricultural practices in spite of economic conditions (see Millington *et al.*, 2008, §3.2–3.3). These behaviours therefore represent the many part-time or 'hobby' farmers (frequently retired) that continue farming practices with other sources of income.

At each time step, SPASIMv1 first uses the ABM to establish which pixels of the landscape grid will be in a crop, pasture or non-agricultural land use. All non-agricultural pixels are subject to change via the state-and-transition component of the LFSM. At each time-step, all pixels in the landscape may be subject to burning. With this model structure, SPASIMv1 may be used to examine scenarios of land-use change, land-tenure change, and climate change and their consequences and interactions with the wildfire regime. For example, Millington *et al.* (2008) used the model to investigate how the spatial configuration of land-tenure configuration influences trajectories of land-use change, and the consequent effects on wildfire risk. The agent-based approach was useful in this situation as it allowed the explicit representation of the consequences of individual decision-makers and their decision-making on spatial variation in land tenure and land cover. Millington *et al.* (2008) found that changes in wildfire risk were not spatially uniform and varied according to land-use composition and spatial configuration, highlighting the importance of considering these changes in a spatially explicit manner as the result of individual agents' actions.

Agricultural land abandonment has been ongoing in SPA 56 with commensurate shifts in land cover to shrub and forest land (Romero-Calcerrada and Perry, 2004). Similar dynamics have been observed across the Mediterranean Basin more widely (Wainwright and Thornes, 2003; Mazzoleni *et al.*, 2004) and the implications of such land-cover change for are unclear due to multiple interactions. Although increasing vegetation cover in Mediterranean landscapes might reduce soil erosion by reducing effective rainfall intensity at the ground surface (Kosmas *et al.*, 1997; Wainwright and Thornes, 2003), it also brings the potential for changes in the frequency and magnitude of wildfire events. In semi-arid environments, thresholds of fire temperature and soil moisture are believed to shift soil hydrophobicity between water repellent and non-repellent states (Doerr *et al.*, 2006; Garcia-Corona *et al.*, 2004). Furthermore, soil-water repellence has been found to be more spatially uniform following more intense fires (Ferreira *et al.*, 2005). Thus, changes in wildfire régimes due to human land-use change will have spatially varying consequences for soil conditions and resulting rates of runoff and soil erosion (e.g. Vafeidis *et al.*, 2007). In turn, these wildfire/soil-erosion dynamics will likely have consequences for future human land-use decision-making. For example, if a field previously abandoned from agricultural use is burned at a severity great enough to reduce water repellency (due to its increased fuel load), potential crop yields in that area may increase. The feasibility (or desire) for an individual farmer to recultivate that field (whether in place of, or in addition to, their other fields) will depend on the particular economic, social and land-tenure-configuration contexts of that farmer (Figure 3), as the results from Millington *et al.* (2008) illustrate. The cumulative effects of multiple decisions like this across a landscape are difficult to estimate analytically, but may be investigated via agent-based simulation. SPASIMv1 is in the initial stages of development, but the agent-based structure of the model means future versions of the model will be able to incorporate representation of the feedbacks from changing soil and wildfire conditions on individual agricultural actors explicitly.

CybErosion

CybErosion is a modelling framework developed by Wainwright (2008) principally for the evaluation of human–environment interactions in a geoarchaeological context, although it is designed to be flexible for a range of applications. The environment is simulated using a grid-based cellular model. Each cell within the model has a set of characteristics which can vary through time. These characteristics are the vegetation type and biomass, soil thickness, soil texture, soil nutrient content, soil moisture and infiltration rate (Figure 4). Vegetation is modelled using functional types characteristic of long-term vegetation change in the Mediterranean region, with logistic growth models whose parameters are functions of climate and interactions with other vegetation and local conditions. Locally, rates of diffuse (splash, creep) erosion are calculated, as are physical and chemical weathering. These processes are all a function of climate, which can itself vary, but there is no current feedback in the model from surface change back to climate variability. At the local neighbourhood scale, simulation of concentrated (rill, gully or channel) erosion is simulated following a D8 steepest-descent flow-routing algorithm. Sediment is transported following the direction given by the flow-routing algorithm and implementing a simplified version of the travel-distance approach of the Mahleran model of Wainwright *et al.* (2008a, 2008b, 2008c).

Agents in CybErosion represent animals, which can be any of a number of types. At present, parameterizations have been developed for cattle, pig, sheep, goat, deer and humans. Each

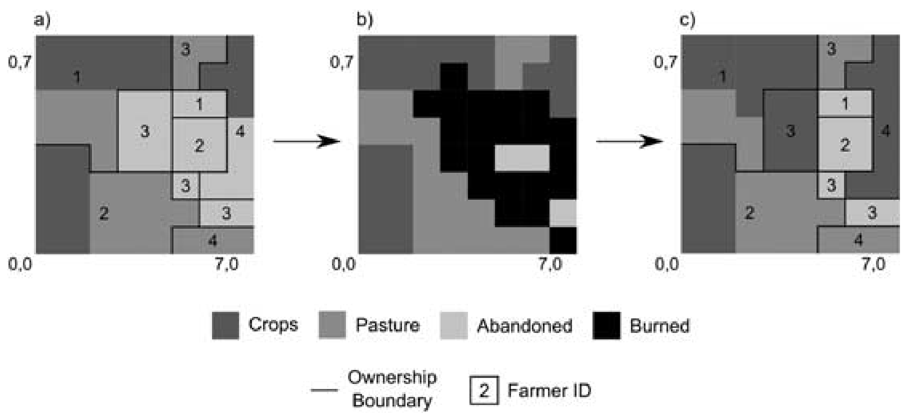

Figure 3. The importance of individual farmer context for agricultural land-use decision-making as derived from an example SPASIMv1 simulation. (a) An example landscape extract made up of 8 × 8 pixels contains land holdings of four farmers with heterogeneous land ownership and socio-economic circumstances. (b) Fire preferentially burns more densely vegetated pixels (e.g. abandoned land). (c) Following a fire event, subsequent use of burned pixels for crops varies between farmers dependent on their individual circumstances and the location of burned pixels as well as their assumptions, such as that burning acts to improve potential crop yields. For example, to increase income whilst minimizing costs of farm fragmentation, Farmer 3 converts six conterminous burned pixels (at coordinates 3,3 to 4,5) to crops, but not individual pixels (at coordinates 5,2 and 7,1). Already with much land under cultivation (in conterminous pixels), Farmers 1 and 2 do not convert their pairs of burned pixels (at coordinates 5,5, 6,5 and 5,4, 6,4, respectively) as the added production does not outweigh the costs of their fragmentation from the remainder of the farm (but if all four of the conterminous abandoned pixels owned by Farmer 2 had burned it may have been worthwhile converting all four to crops), while Farmer 4 finds the fire makes coterminous pixels of formerly abandoned land profitable for cultivation, and so expands from their existing cultivated area.

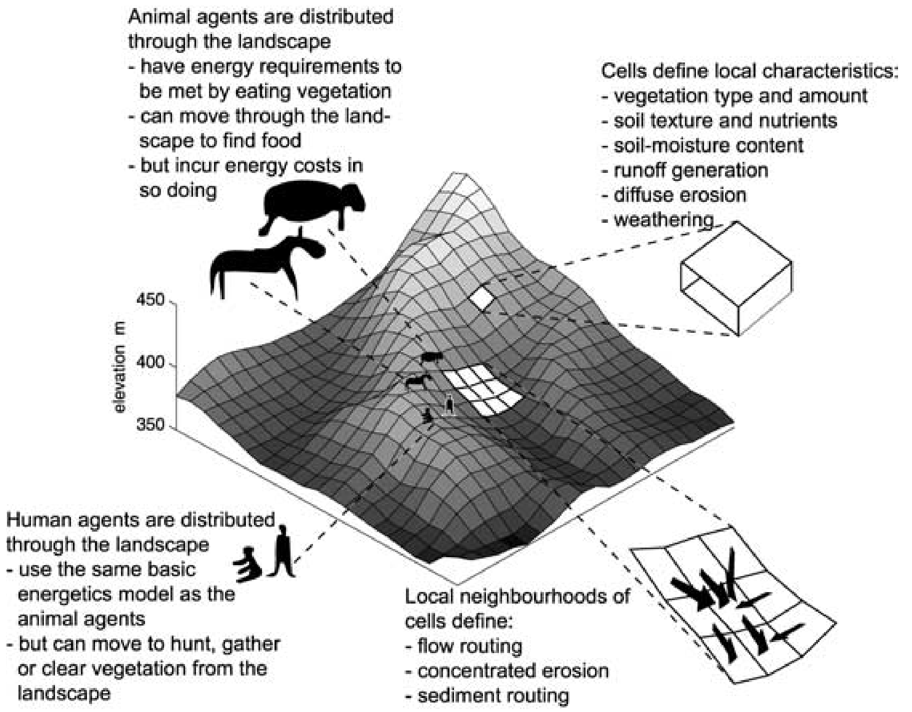

Figure 4. Structure of the CYBEROSION modelling framework (Wainwright, 2008).

agent has an energy requirement which is a function of its body weight and point in life cycle. This energy requirement must be met by consuming food from the environment, and animals can move through the environment in order to find food sources, but in so doing, they undergo an energy cost which must be balanced by the consumption of more food. A simple assumption of 'perfect' perception of the (local) environment is presently built into the model, so that animals will move into an adjacent cell once it contains more food to consume than the presently occupied cell, and will scan the local Moore's neighbourhood to evaluate which is the optimal cell to move into. Clearly this approach does not build other more complicated behaviours into the model, but it does avoid having a stochastic approach to movement through the landscape (the only stochastic element is where two adjacent cells have equal resource levels). In addition, the human agents follow a set of behaviours that allow them to hunt animal agents, or to carry out other activities (at present, simple agriculture or leisure). All agents have realistic simulations of reproductive cycles. Each agent represents an individual, although there is a simple representation of the development of herds.

Interaction between agents and the environment is specifically carried out through the vegetation component, with feedbacks to other processes mediated through the vegetation cover. All agents consume vegetation for food. In addition, human agents will deliberately clear arboreal vegetation from certain areas in order to grow cereals. The present version of the model incorporates no direct decision-making in terms of which might be better areas for cultivation, although there is a feedback in the sense that if cultivated areas produce insufficient returns (e.g. through erosion-induced water or nutrient limitations), a decision to move to other areas for hunting or further cultivation will be required.

Application of the model so far has been limited to evaluating the settlement and environment of the prehistoric site of Roucadour, Lot, France (Gascó *et al.*, 2004; Wainwright *et al.*, 2006). Roucadour provides an interesting case study because it represents an early site where agriculture was practiced regionally (Niederlender *et al.*, 1966), but where recent re-evaluations have demonstrated the continuation of hunting over a significant period as an important economic activity (Gascó *et al.*, 2004; Lesur *et al.*, 2001). Furthermore, local erosion rates can be seen to have been highly variable in both space and time, in a way that suggests human influence is the dominant controlling factor. Wainwright (2008) concluded that the model was able to demonstrate emergent behaviour in relation to spatial and temporal patterns of erosion (Figure 5). Landscape evolution in this sense is the result of complex responses that cannot be simply predicted from the initial conditions and estimates of population from the archaeological data (Figure 6). Indeed, an important rôle for the model may be in testing different scenarios based on uncertainties in the palaeoenvironmental reconstruction and archaeological interpretations. One significant result of the modelling so far is the inherent instability of small populations (Figure 7) in relatively small landscape areas [but larger than what has traditionally been considered to be the area of a 'site catchment' (Jarman *et al.*, 1982; Vita Finzi, 1978)], suggesting the importance of human population mobility in periods of initial agriculture.

Discussion

These two case studies demonstrate the advantages of agent-based approaches over other methods for evaluating human–landscape interactions. Both are based on representations of the system that are consistent with a process-based modelling approach – SPASIMv1 based on markets and CYBEROSION on energetics – which enables a focus on developing a rich understanding of the interactions. By representing heterogeneity in individual actors' actions, they can represent dynamic feedbacks in the interactions in a way that is otherwise difficult or impossible (although it could be argued that a number of important feedbacks are still missing from both models).

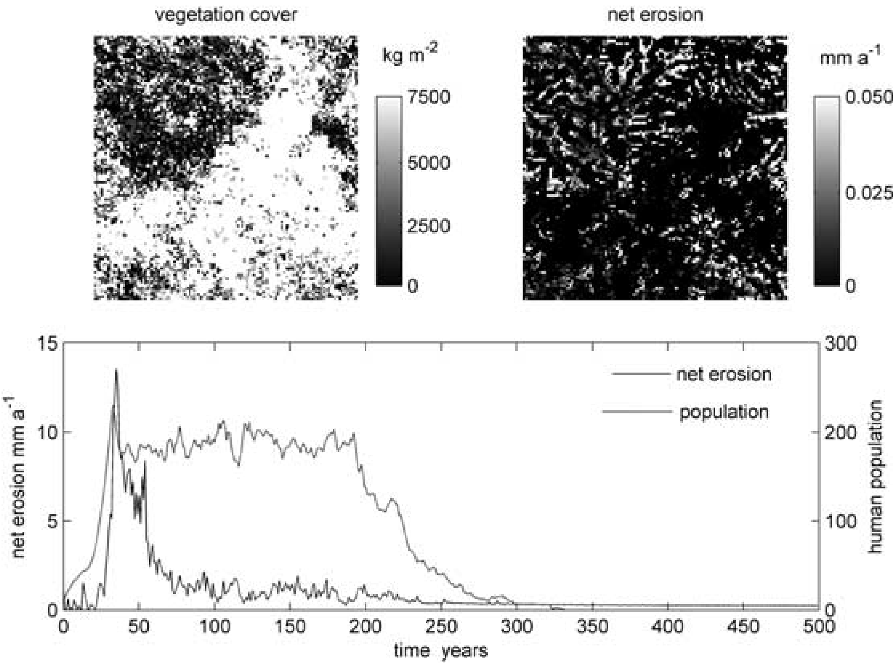

Figure 5. Results of the CybErosion model as applied to the landscape around the prehistoric site of Roucadour (Lot, southwest France). The upper figures show maps of simulated vegetation cover (starting from a uniform cover) and simulated net erosion after 50 simulated years with 1000 initial animal agents and 10 initial human agents (run 4 of Wainwright, 2008), with a pixel size of 90 m. The lower figure shows the evolution of the net erosion rate and human population through time.

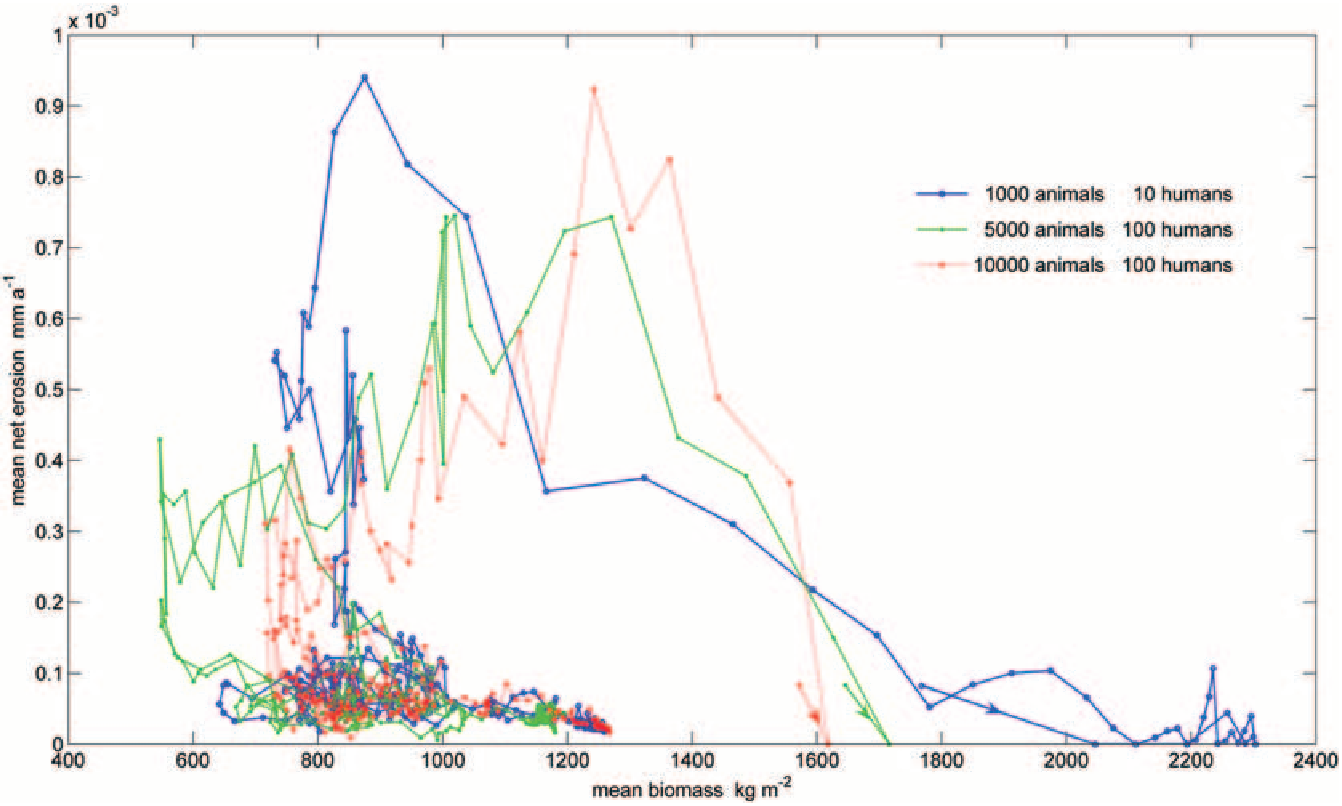

Figure 6. Modelled relationship between mean landscape biomass and mean net erosion rate as a function of different initial numbers of animal and human agents in CybErosion. Results show effects of path dependence and non-linear relationship between biomass and erosion rate. Biomass is used as the independent variable as climate is constant through the simulations, and the effect of agents on landscape evolution is mediated through vegetation cover in the model. The arrows show the direction of initial evolution of the simulation in each case.

However, the role of modelling in evaluating which are important feedbacks may come to the fore here. These models highlight the importance of complex landscape response, thresholds and path-dependencies. For example, in SPASIMv1 agricultural land-use area decreases dramatically when a critical threshold in the fragmentation of land tenure (i.e. ownership) is crossed (see figure 4 in Millington *et al.*, 2008). The importance of previous land-use decisions on later decisions because of chance events (e.g. a fire) was also demonstrated (Figure 3). In CybErosion, areas of focussed human activity

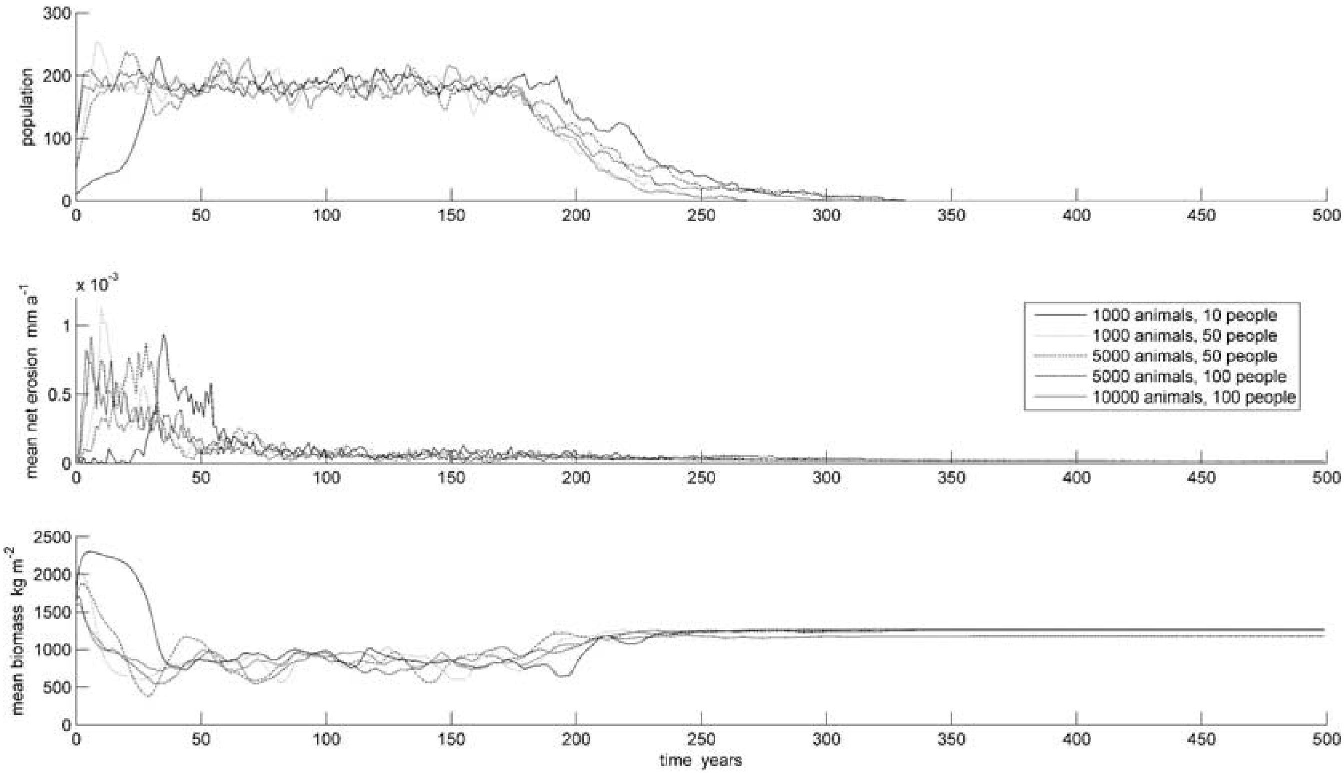

Figure 7. Sensitivity of results of the CybErosion model to initial numbers of agents as applied to the same landscape as Figure 5. Model runs with base parameters as defined in Wainwright (2008). The lack of movement of human populations seems to produce an extreme sensitivity in the landscape producing population collapse after 268–330 years.

were noted as emerging within the landscape without any specific incorporation of this activity in the model or the rules base. The relative timing of initial conditions in relation to different populations also significantly changed predicted amounts and patterns of erosion (Wainwright, 2008). As rates of modelled erosion vary significantly as a function of initial conditions and path dependency (Figures 5–7), landscape evolution can be seen to be dependent on understanding past human occupation and decision-making and their variability.

Models of this sort also have a significant part in the synthesis and communication of understanding both between modellers and non-modellers and between scientific disciplines. In this way, models of this type can also assist interdisciplinary and multidisciplinary research. For example, 'companion modelling', exemplified by the work of the CORMAS research group (Barreteau, 2003), uses high levels of participation by non-modellers in the construction and use of its ABMs of land-used change. Methods such as role-playing games are used during model development and analysis (e.g. Castella *et al.*, 2005; Castella, 2009). The CORMAS approach has been advocated as an ideal way to develop 'realistically descriptive specifications of individual behaviour and social interaction', promote learning and understanding, and aid negotiation processes (Moss, 2008, abstract). Souchère *et al.* (in press) recently used the companion approach to examine the management of erosive runoff due to agricultural land use in France. As an extension of this approach, computer-mediated role-playing games allow stakeholders to take control of agents within an ABM for teaching and education, to foster collective learning and identify group behaviour to solve common problems, or for researchers to observe the behaviours of participants (Nguyen-Duc and Drogoul, 2007; Guyot and Honiden, 2006). With regard to interdisciplinary and multidisciplinary research, the object-orientated programming framework an ABM approach demands simultaneously provides modularity and flexibility to explore multiple model structures and linkages with other models and model types, potentially from other scientific disciplines. For example, the People and Landscape Model (PALM) uses routines from previous models to represent organic matter decomposition (CENTURY) and water and nitrogen (DSSAT) with household agents to examine interactions between biophysical and socio-economic components of a landscape (Matthews, 2006). Yadav *et al.* (2008) also discuss different ways in which the CENTURY model can be used within an agent-based framework in both online and offline modes in order to evaluate the ecological impacts of LUCC decision-making.

Agent-based approaches may also highlight future research needs – especially in areas that cross-cut traditional disciplinary boundaries and may not otherwise be picked up. For example, upon completion of the initial version of the model, we returned to the study area with maps produced by SPASIMv1 to discuss them with local farmers and other interested parties. From these meetings we were able to learn about potential shortcomings in the model and ways to improve representation of the decision-making component, notably the locals' desire to see some representation of potential future urban change. Such a method is clearly not possible with the CybErosion application presented here, but discussion of its results with archaeologists and palaeoenvironmentalists has allowed initial theories to be addressed and refined, with corresponding developments to be suggested for the modelling. The development of CybErosion has required the integration of concepts and empirical data from a range of disciplines including agronomy, ecology, anthropology, archaeology, economics, computation and psychology as well as geomorphology. As such, it enables the integration of theory and the development of new models by addressing the tensions between information from disciplines, and from the emergence of commonalities between them. The use of a bottom-up approach also adds to the sense of place (e.g. Beven, 2000) and emphasizes the significance of local variability over (or in combination with) global drivers. In this way, they enable a rich interpretation of landscapes and their history.

Although modelling approaches such as those described here provide benefits for interdisciplinary and multi-scale investigation, the integration of data and perspectives from different disciplines may not always be as straightforward as at first might be hoped. For example, in discussing the potential of integrating ecological and economic models, Drechsler *et al.* (2007) suggest that ecologists will need to be aware that analytical tractability is valued more highly in economics than is predominantly the case in ecology, but that economists will need to prepare themselves for greater model complexity than that to which they are accustomed (see also Anon., 2009). Differences in perception and understanding of the systems under consideration are likely to arise as geomorphologists engage in collaborations with scientists and modellers from other disciplines including economic and the social sciences. Furthermore, the differences are equally likely to be as much about the objectives and potentials of the models being developed. Whereas geomorphologists may be happy examining landscape evolution over durations of centuries, economists and social scientists will be more comfortable over decadal extents. Models that have examined the interactions of past civilizations with their environments have tended to examine longer time periods [e.g. Axtell *et al.* (2002) and CybErosion (Wainwright, 2008) ran their models for 550 and 500 years, respectively] than models considering contemporary human populations [e.g. An *et al.* (2005) and SPASIMv1 (Millington *et al.*, 2008) here considered 19- and 28-year extents, respectively].

There are also a number of disadvantages or limitations of the ABM approach. It tends to be computationally intensive, notwithstanding the technological developments mentioned earlier. The application to larger areas or populations may be limited unless significant amounts of computer power are available, or aggregation of agents is carried out (see later). It has been noted that individual behaviour does not (always) represent or allow emergence of social behaviour (O'Sullivan and Haklay, 2000). In more complicated models, there is thus a danger of building in too many rules of behaviour in an attempt to overcome this limitation, and at the same time too much complexity reduces the heuristic value of this modelling approach. A key area for further research is thus how to overcome this limitation. Rule-based models are also limited in their flexibility and ability for agents to 'learn' behaviours, an issue that has been at the heart of the artificial intelligence literature for several decades, despite advances in evolutionary computation (Edmonds, 1999). It may be very difficult to build in sufficient complexity to represent an appropriate range and detail of factors that affect the decision-making process in current and future LUCC (Parker *et al.*, 2008a). For example, what human incentives might we need now and in the future to ensure sustainability of different aspects of the environment, such as landscape change and aesthetics, and ecosystem services? Furthermore, as the differentiation of indifferent and interactive kinds highlights (e.g. Hacking, 1999), actors that are cognisant of their representation in a simulation model may modify their behaviour upon interpreting model results, invalidating the original assumptions upon which the model was built! One should certainly avoid the trap of trying to build 'models of everything' (Wainwright and Mulligan, 2003), and remember that a model should be produced for a specific purpose (which is not necessarily a forecast). An important part of the process of modelling is the conceptualization of what are considered to be the most significant aspects of the system to capture its real-world behaviour. There is also the potential for overinterpretation of results of 'emergence' (e.g. Sawyer, 2001) and self organization (e.g. Frigg, 2003).

A number of major challenges present themselves if ABMs are to be a useful tool in the development of an integrated cultural geomorphology. In the introduction, it was noted that one of the major limitations of current approaches is their overdependence of case studies, yet we have chosen to illustrate our points with two very different case studies in this paper. We would argue that the difference lies, though, in the conceptual (process-based) underpinning of the case studies and in the maturity of the development of different methods. ABMs as applied to geomorphological questions are very novel, and ABMs in a broader sense are only a recent methodological development. At one level, the utility of this methodology will only be accepted once its explanatory power has been demonstrated in a number of specific examples, and only when this has been achieved will it be possible to develop a general theory. Moss and Edmonds (2005a, 2005b) suggest that this sequence will be the case for ABMs of social systems in general. In the meantime, it is important that issues relating to the communication of model algorithms, structure and results are addressed [as noted by Grimm and Railsback (2005) for IBMs in ecology and Grimm *et al.* (2006) for IBMs and ABMs in general, and the production of model 'ontologies' as discussed in the computer-science literature (e.g. Parker *et al.*, 2008b)]. For example, Liverman and Roman Cuesta (2008) note that different methodologies in LUCC studies in general have made it difficult for comparisons to be made and theoretical or conceptual generalizations to be drawn. In the short term, the most valuable contribution of agent-based approaches to geomorphologists may be in the 'companion' mode (as outlined earlier) as a means to investigate decision processes and coordination among actors in geomorphological processes. Once such approaches are taken, it will be possible for geomorphologists to reconceptualize and address medium- to long-term implications of human activities on the landscape, and thereby produce a coherent 'cultural physical geography', as called for by Gregory (2000).

Many of the challenges posed relate to issues of scale and scaling. The applications demonstrated in this paper still operate over relatively small spatial (few hundreds of kilometres squared) and temporal (decades-centuries) scales. These models run comfortably on a reasonably powerful personal computer, albeit with run times requiring several days. These run times currently limit replications of model runs, but there is no reason why parallelized versions of the models should not run significantly faster with present technology. In terms of timescales, current applications are appropriate for the assessment of decadal policy implications, or the medium-term impacts of land-use change; they are most appropriate for evaluating knowledge of the system and problem-framing (e.g. Anon., 2009) than for direct prediction. Faster models would also more easily be applied to larger spatial studies, although the increase in number of agents produces a highly non-linear increase in computing resource required because of the large overheads required in agent–agent interaction. Conceptualizations are thus required that allow the approach to be applied over larger areas by using agents that represent larger entities than just the individuals or households as used here. Agents may be used to represent entire settlements (e.g. Sanders *et al.*, 1997), or national and international organizations (e.g. Manson, 2005). However, there is an unresolved question in that it is unclear when these larger scale agents just become spatially distributed econometric or game-theory models, although Axelrod (1997) has demonstrated that this limitation does not always occur.

Parker *et al.* (2008a) have highlighted the major problems relating to spatial mismatches between processes. While the compound actions of individuals at the local scale may have significant effects at the global scale – most obviously with the case of enhanced greenhouse-gas climatic changes – it is unfeasible other than with significant aggregation to simulate the global-scale feedbacks using an ABM, although developments in parallel computation may mean that this limitation will be overcome in the near future (and indeed already have in simulations of disease spread: Epstein, 2009). Whether this approach is better than the reconceptualization associated with aggregation is moot. The modeller must therefore in this case impose boundary conditions on local simulations that will have a significant impact on the behaviour of the model. Again, there are major issues of whether any 'emergent' patterns thus observed are a response of the system or of the imposition of more-or-less artificial boundary conditions. Scale mismatches will also occur temporally, and O'Sullivan and Haklay (2000) have noted a similar problem in specifying the initial conditions of the behaviours of agents, inasmuch as they will be highly constrained by past contingencies and path evolution. Projecting behaviour of individuals within modern societies over long time extents is likely to be difficult in the context of rapid changes in technological developments and national and international policies on climate change and energy use. However, perspectives that the effects of globalization on individuals' behaviour are only a modern phenomenon may be overstated (e.g. Champion, 1989; Peregrine, 1996). As noted earlier, geomorphological applications of ABMs sit in what might be an uncomfortable disjuncture between the comfort zones of modellers happy to work at century to millennial scale (or even longer), such as ecologists and Earth scientists, and those happier considering decades or less, such as economists. It may therefore be necessary to distinguish between more heuristic and theoretically based models (e.g. more at the CybErosion end of the spectrum), which would aim to simulate landscape evolution over centuries, whilst empirically based models that explore policy options (e.g. akin to SPASIMv1) might be more appropriate for considering change over decadal timescales.

The use of generative, bottom-up models to represent feedbacks between heterogeneous human actions and geomorphic process is likely to throw up questions about how best to evaluate ABMs. Issues of 'validation' of this sort of model have a broader significance, not least because ABMs are increasingly frequently used as part of decision-support systems (e.g. Zacharias *et al.*, 2008) and other means of defining policy, with all the related dangers pointed out by Oreskes *et al.* (1994). Pattern-matching of model output with empirical observations at a single scale or level of organization is unlikely to provide sufficient detail about representational accuracy. A pattern-orientated approach that compares model and empirical data at multiple scales and levels, as advocated by Grimm *et al.* (2005), is more likely to improve confidence about the fidelity of model output. Moss and Edmonds (2005a, 2005b) have suggested a similar approach for the evaluation of sociological ABMs, but here emphasis should remain on ensuring appropriate model calibration over precise forecasts of future system states (Moss, 2008).

Conclusions

Geomorphology as a discipline must engage with the fundamental need for a better understanding of the linkages between people and geomorphic processes. This understanding is vital for the development of deep understanding of Holocene landscape evolution, and especially given the accelerating rates of impacts over the last few centuries. As there is no indication that this acceleration will change significantly, the discipline needs to address the challenge of providing the science that can contribute to major questions of global importance. Human activity in general and specifically LUCC have significant impacts on geomorphic processes with corresponding implications for the sustainability of ecosystem services (e.g. prevention of soil erosion, mitigation of natural hazards such as flooding) and on global climate change (e.g. albedo feedbacks following erosion of agricultural land or rangelands in drylands). To address these issues of global importance, geomorphologists need to develop more conceptually coherent and multidisciplinary approaches.

ABMs provide a means by which narrowly empirical approaches to human–landscape interactions may be transcended. The examples presented here demonstrate that ABMs can be useful both in a policy-related sense, and from a heuristic sense of attempting to develop more conceptually informed world views. The agent-based modelling framework provides a means of investigating complex landscape responses to individual, context-dependent and heterogeneous human decision-making, and the potential to incorporate agents who have geomorphic impacts directly into scientific research (via participatory approaches). As ways of integrating existing knowledge bases and for evaluating potential contradictions between existing theories, or between theory and observation, they are a vital part of bridging a significant gap in the current discipline in the evaluation of physical and social mechanisms of landscape evolution.

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