PHILOSOPHICAL TRANSACTIONS OF THE ROYAL SOCIETY B

Phil. Trans. R. Soc. B (2012) **367**, 259–269
doi:10.1098/rstb.2011.0187

Review

From actors to agents in socio-ecological systems models

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The ecosystem service concept has emphasized the role of people within socio-ecological systems (SESs). In this paper, we review and discuss alternative ways of representing people, their behaviour and decision-making processes in SES models using an agent-based modelling (ABM) approach. We also explore how ABM can be empirically grounded using information from social survey. The capacity for ABM to be generalized beyond case studies represents a crucial next step in modelling SESs, although this comes with considerable intellectual challenges. We propose the notion of human functional types, as an analogy of plant functional types, to support the expansion (scaling) of ABM to larger areas. The expansion of scope also implies the need to represent institutional agents in SES models in order to account for alternative governance structures and policy feedbacks. Further development in the coupling of human-environment systems would contribute considerably to better application and use of the ecosystem service concept.

Keywords: socio-ecological systems; agent-based modelling; social survey; spatial scaling; human behaviour; decision-making processes

1. INTRODUCTION

There is increasing recognition of the need to represent human behaviour and decision-making processes in models of complex socio-ecological systems (SESs) [1]. This includes behaviour at the individual and household levels, as well as the emergent (adaptive) properties of SESs that are reflected in institutional behaviour, policy formation and the broader attitudes of society. Frameworks for SES models increasingly seek to address the characteristics of people and their dynamic interactions with the environment [2]. The anthropocentric nature of the ecosystem service concept, for example, has gone some way to re-focusing attention in ecosystem analysis from the ecology of 'nature' to the important influence of people [3]. Notions such as ecosystem service beneficiaries are used to reflect that the attributes and roles of the people within SESs are at least as important as the attributes and roles of other organisms [4].

As new ways of thinking about SESs evolve, there will be an increasing need to empirically ground SES models with data not only about the biophysical components of the system, but also about the human dimensions. The term 'empirically grounded' model is used here to refer to the systematic identification of process representations through inductive or deductive methods as well as calibration and validation of models that encapsulate these process representations. Social-survey data are fundamental in achieving this goal, especially in setting model boundary conditions, identifying plausible human behaviour and establishing decisional outcomes. Empiricism cannot, however, achieve everything, which is why SES models are important. Models can be used to integrate different data sources, different representations of human decision-making and can then be leveraged to interrogate the system in areas where data are limited. Thus, within this paper we:

- explore how SES models can be empirically grounded using information from social surveys;
- outline alternative ways of representing human behaviour and decision-making in SES models; and
- discuss how human behavioural models might be generalized beyond their 'empirically grounded space' for application over large geographical areas.

Further development in the coupling of human and ecosystem models within an SES paradigm would contribute considerably to on-going global change debates that are played out at national, continental and global scales. Top-down, equation-based approaches to modelling SESs are unlikely to be sufficiently representative of human decisional processes, and model development is likely to be incremental rather than stepwise [5]. Likewise, traditional economic models of human decision-making based on optimizing behaviour have little further to offer in terms of understanding the role of people in modifying landscapes. An iterative and integrative modelling, data collection and analysis approach are required to address the limitations of existing SES models, and a discussion of these new approaches is the purpose of this paper.

Here, we discuss the application of agent-based modelling (ABM) as the focus for discussion, findings and understanding of SESs. Specifically, ABM provides

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One contribution of 16 to a Discussion Meeting Issue 'Predictive ecology: systems approaches'.

a novel approach to representing feedbacks between human and environment systems that can provide new insights and improve our understanding of SESs. The ABM approach is computational and involves the creation of virtual objects with autonomous behaviour (i.e. agents), to represent real-world actors and their interactions amongst each other and with their environment. While flexible in representing complex systems that include human and ecological processes [6], the ABM approach may also provide a one-to-one mapping between virtual and real-world entities that makes the approach appealing for calibration, validation, prediction, and the exploratory and explanative modelling of complex systems. The approach has been used for theoretical developments and to guide empirical research and evaluate plausible scenarios, e.g. [7]. As such, ABM has a major contribution to make in the future of SES models.

One of the areas where ABM will play a major role in SES research is in the representation of institutional and governance structures. Since many ecosystem services are intangible, changes in their provision may not be obvious until a specific threshold is crossed (e.g. groundwater depletion). When this occurs (owing to scarcity, over consumption or changes in external factors), a governing body is typically required to coordinate the restoration of the service. Similarly, it is typically a governing body that monitors the changes in the provision of an ecosystem service so as to mitigate any disruption to the service. In some cases, the market plays a role in this process, but we know that markets work differently in relation to public goods (e.g. tragedy of the commons [8]). This suggests that the representation of institutional and governance structures in SES models is crucial to understanding the ways in which organizations and policy provide feedbacks to agent behaviour. At present, there are few agent-based models (ABMs) that explicitly incorporate macro-level formal institutions or governance bodies (e.g. government) as agents such that there is a hierarchical interaction across scales between individuals and institutions. As a necessary first step to incorporating governing agents in SESs, the governing organization or authority typically imposes specific actions on the agents, which acts more like an exogenous parameter setting than an interacting agent (e.g. [9]).

This paper uses a review of the relevant literature with specific examples to discuss the use of ABM in simulating SESs. We explore the ways in which ABM represents human behaviour and how social-survey data can be used to provide the empirical basis for model design and application. We also discuss how ABM might be applied at different spatial scale levels, with the aim of moving away from traditional landscape-based case studies.

2. REPRESENTING HUMAN BEHAVIOUR AND DECISION-MAKING IN SOCIO-ECOLOGICAL SYSTEM MODELS

ABM has emerged as an appropriate tool for representing human decision processes, especially with respect to the land system as an exemplar of human–environment interactions [10–14]. ABM came out of thinking in the 1970s within the artificial intelligence (AI) research community [15] and has become increasingly popular in the social sciences and land system science [16–19]. In early agent-based models (e.g. [20,21]) the desired agent behaviour was derived from the simplest possible set of rules. More recently, however, ABM has become increasingly complex and this evolution has been associated with attempts to empirically ground the representation of human behavioural processes (e.g. [22–24]) which has led to models with increasing specificity with respect to individual case studies [25].

An agent is a computational representation of a real-world actor, which could be used to represent, amongst other decision-making or behavioural entities, a person, a household, a firm, an organization, an animal or a plant. The structure of an agent is typically formed by a combination of descriptive characteristics: a set of behaviours (e.g. decision-making structures, actions/responses, goals and mental maps), and a set of constraints and labels identifying types and roles. An agent-based model, within the context of SES change, is then composed of a population of agents and a landscape within which they act and interact. A description of these components is provided here along with examples illustrating how social-survey data have been used to empirically ground agent and ABM components within the context of SES modelling.

ABM can be used to formalize computationally *a priori* knowledge of the system by creating a suite of conceptual- and theory-driven models (sometimes termed toy models, figure 1). These models are used to evaluate key research questions and to determine the conditions under which complex spatial and temporal patterns in management behaviours and subsequent ecosystem properties can emerge from a limited set of behaviour–response functions. For example, the environment behaviour theory (EBT) defines behavioural intention based on situational, psychological and social-environmental factors [26].

Results from conceptual models provide new knowledge about how SESs may change in simple contexts (e.g. situation). The modelling process is iterative, with each cycle—through figure 1—providing an opportunity for refinements such as: incorporating new data and findings from social surveys and ecological fieldwork; adjusting the conceptual framework and hence the agent-based model; adding geographical information systems and social-survey data to the agent-based model; integrating with ecological models; experimenting with different decision-making, learning and adaptation strategies for different actors in the system. The combined understanding of the decision-making structure and rate of knowledge adoption provides insights that the model can leverage to better simulate agent behaviour or practices. Each iteration through the process (of figure 1) allows new 'what if' questions to be posed and tested.

ABM is especially well suited to interaction with social-survey data since both the models and the data are inherently qualitative. ABM may include quantitative, equation-based approaches, but the rules that characterize this approach are qualitative. The key components of agents to be modelled are: the rate of agent creation, decision-making strategies, the drivers of behaviour, agent types and their

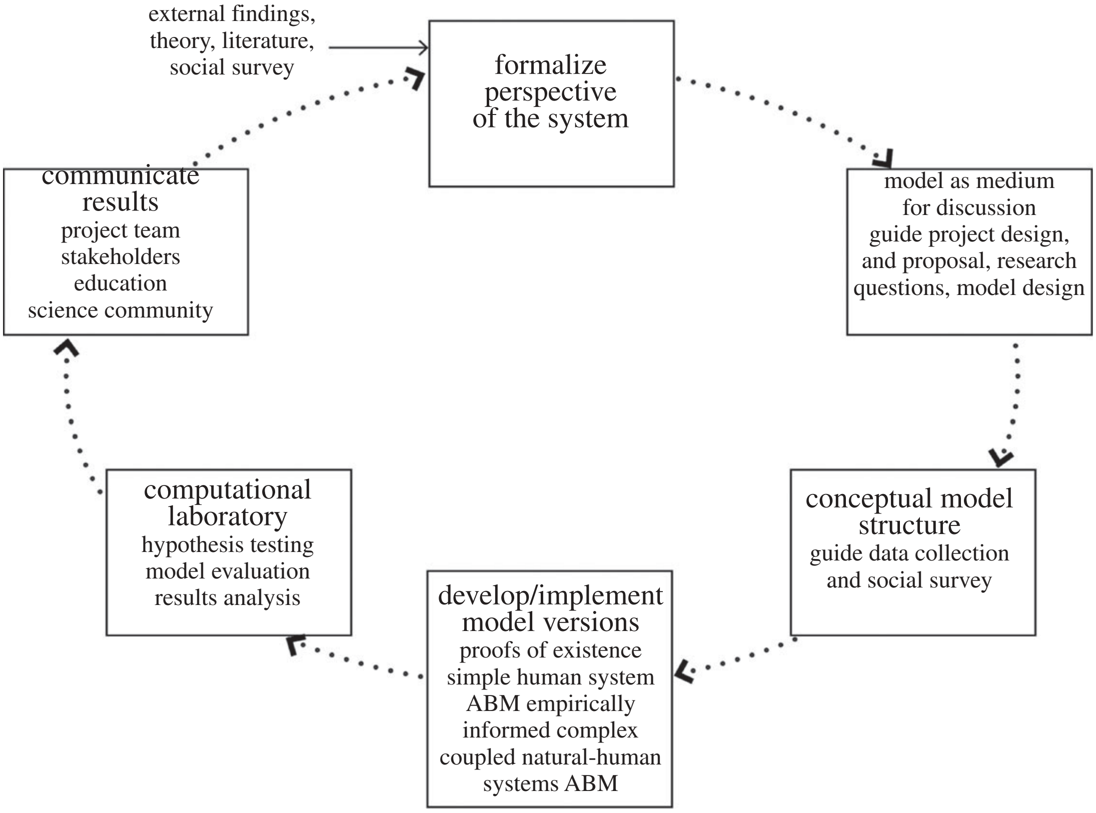

Figure 1. The agent-based modelling process as an approach to scientific enquiry.

characteristics. All of these model components can be informed empirically using social-survey methods.

There are many social-survey methods based on interviews and questionnaires that range in scope. These include semi-structured interviews and structured approaches to collect categorical data. Some form of respondent mapping is also usually applied to establish basic socio-economic attributes. In terms of empirical ABM development, the crucial methodological step is often associated with translating qualitative social-survey outputs either into qualitative agent rule bases defining, for example, preferences, values or strategies, or into parameter-based algorithms (e.g. calculating agent utility functions). Quantitative methods tend to seek to assign parameter weights to values of judgements. Qualitative methods based on coding approaches are, however, at least as important in defining qualitative agent rules, especially with respect to non-economic behavioural factors.

3. EMPIRICALLY GROUNDING AGENT-BASED MODELLING, USING SOCIAL SURVEYS

(a) *Agent attributes*

The characteristics of an actor, such as age, income, education and marital status, influence its decision-making and subsequently the SES within which it is situated. Identification of the actor characteristics that are relevant to SES processes is one of the goals of using social surveys to empirically ground ABM. Mapping *actor characteristics* to their agent counterparts, for which we use the term *agent attributes*, defines the level of agent heterogeneity in an agent-based model, and often the agents' attributes are used to classify them within a typology or to drive specific actions and decision-making behaviour. The ability to represent heterogeneity in agent attributes within an agent population and the individual outcomes and interactions that result from that heterogeneity is a key quality that sets the ABM approach apart from equation-based models. In equation-based modelling (EBM), it is possible to incorporate stochastic elements and age- or life-stage transitions in dynamic population models, but individual characteristics and interactions are lost as EBM typically represents an average or 'typical' agent (see [27] for a full comparison of EBM and ABM).

The acquisition of data describing the characteristics of human populations via social-survey approaches (e.g. census data) typically tell us little about the actions, reactions and decision-making strategies that actors employ within a population. Efforts to use these data to predict preference weights that inform location-based decisions are often unsuccessful [28,29]. While identifying the types of preferences that can be explained via respondent characteristics is a research question that remains to be addressed, agent attributes do play a critical role in SESs in a variety of ways.

First, agent attributes may act to enable or constrain behaviour. In many regions, the age of an actor defines its ability to drive legally, to consume alcohol and to retire. Whether the reference point is age, household demographic stages, education or records of past experiences, actor characteristics provide capabilities or constraints on the agents' behavioural rules.

Second, changes in agent attributes may alter the decisions that are made. This approach has been used to estimate the impact of population growth on panda habitat in Wolong Nature Reserve, China [30] by

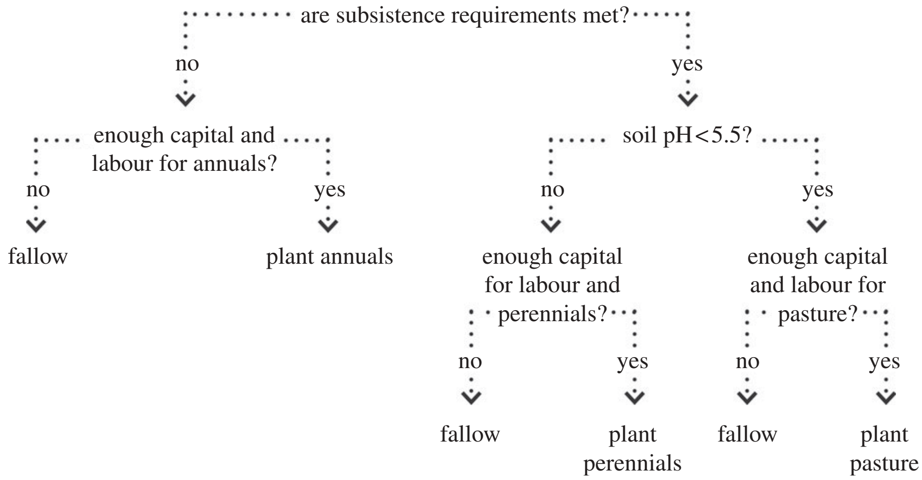

Figure 2. General heuristic decision tree of household decision-making in LUCITA (Deadman *et al.* [37]). Reprinted with permission from Pion Ltd., London.

triggering changes in agent attributes that arise from changes in the household demographic profile through time. As agents age and change their marital and family status, they also change their resource consumption behaviour and the subsequent impact on forest cover and panda habitat. The distribution of household sizes, timing of behavioural changes, resource extraction levels and contextual factors driving decisions were empirically grounded using survey data from several sources, including 220 local households.

Third, knowledge of agent attributes by other agents may provide a signal or an identification 'flag' [31] that acts to enable or prevent interactions from occurring. In some cases, flags may identify specific types of agents (e.g. male, female, household, developer, etc.) and, in others, they can promote or inhibit interactions between agents sharing the same classification type (e.g. marital status, education level).

(b) *Decision-making strategies*

A number of theoretical representations of decision-making strategies have been used to provide agents with cognitive abilities. Such strategies include: heuristics [32], bounded rationality [33,34] and utility maximization [17] and evolutionary processes [35].

(i) *Heuristics (decision trees)*

One of the simplest approaches to represent decision-making in an agent-based model is through the use of heuristics or decision trees. Heuristics involve Boolean evaluations of a variable or measurement that returns a true or false result and a subsequent action. The approach is implemented using simple 'if... then... else...' statements that closely correspond to conceptual decision-making models. Unlike the 'black box' approach to decision-making used in genetic algorithms or neural network solutions ([36], see §3*b*(iii)), heuristic strategies provide a transparent view of the decision-making process and therefore aid in the understanding of the human–environment relationships being modelled.

The simplicity of the approach also lends itself to empirical-grounding with a range of qualitative or quantitative data. In the Land Use Change In The Amazon project (LUCITA), a spatially explicit agent-based model was developed to investigate the degree to which farm-household demographics explained the rate and extent of deforestation along the Trans-Amazon highway [37]. The model comprises farm-household agents that make cropping decisions based upon their capital, labour and soil quality endowments, which change as a function of time spent farming (i.e. capital accumulation), household demographics (labour pool and subsistence requirements), labour market and crop selection.

Social scientists conducting long-term survey research in the Altamira region of Pará identified three overarching decision questions that guide farmer behaviour: are subsistence requirements met, is the soil suitable for arable crops and does the household have sufficient capital and labour resources to undertake farming? As part of these overarching decisions, a range of household characteristics were recorded that included amongst others the timing of arrival, demographics, level of farming knowledge and capital resources when arriving in the area from other regions of Brazil.

A simple decision tree reflecting the qualitative nature of the three overarching decisions was derived from a number of surveys and this is used by the farm-household agents within the LUCITA model to determine what type of crop to farm or whether to leave a field fallow (figure 2). The heuristic approach is interesting in that it mixes qualitative survey findings with quantitative metrics to implement behaviours. Qualitative and quantitative mixing is often necessary when continuous data are used in combination with decision outcomes based on threshold values. For example, farm-household subsistence requirements provide quantitative constraints on farm-household agent behaviour that are met through the area of annual crops and capital accumulated from other crop sales or off-farm labour activities. In contrast, the authors of LUCITA imposed a quantitative threshold used as a proxy for qualitative behaviour that was not directly recorded by survey and too difficult to implement within the model. The authors took expert

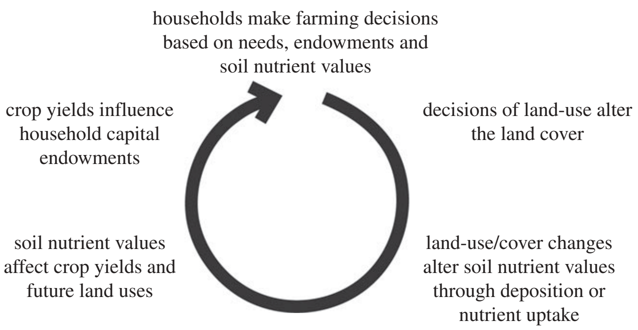

Figure 3. Cyclical feedback process of a coupled human-environment system within the context of land-use change and farming.

knowledge that farmers in the region determine soil quality based on existing vegetation and soil colour and texture [38,39], and incorporated soil quality evaluation into the agent decision-making by using the pH values that were produced from crop models and soil information. The use by agents of pH values to distinguish between good and poor soil quality incorporates a feedback between crop choice and nutrient limitations that couple the human-environment systems within the context of land-use and land management (figure 3).

(ii) *Utility maximization and bounded rationality*

Traditional economic theory, based on the ideas of *homo-economicus* and rational decision-making, assumes that individuals make rational choices to maximize their utility under conditions of perfect information [40]. While the idea of utility maximization can be disputed, there are strong arguments against the assumption of the availability of perfect information. Not only is the availability of perfect information unlikely, but humans are also unable to process the large number of possible combinations that are required in complex decisions as assumed in perfect rationality [41]. Due in part to these arguments, most ABMs of SESs represent agent decision-making with utility-based approaches assuming bounded rationality. Bounded rationality in its simplest form involves creating a subset of all possible outcomes that represent a reasonable selection of options over which an agent makes a rational decision [42].

A bounded rational approach to decision-making has been implemented by a suite of ABMs that represent residential settlement [43] and exurban development in southeastern Michigan [44,45]. The residential settlement model (named SOME) uses a utility-based approach that is empirically grounded with a social survey conducted in the Detroit region [28]. Through factor analysis, survey questions were reduced to identify three factors driving residential location decisions at an appropriate scale of representation, which were: nearness to schools and work, the aesthetic quality of the landscape and neighbourhood similarity. The factor scores for each of these factors were rescaled and used as preference weights in the following utility function:

$$u_{r(x,y)} = \prod_{i=1}^{m} (1 - |\beta_i - \gamma_{i(x,y)}|)^{\alpha_{ir}},$$

where $u_{r(x,y)}$ is the utility agent r acquires from the grid location (x,y); m is the number of factors evaluated by the agent, which is three in this case; β_i is the preferred value for factor i, which is assumed to be 1 for each factor and represents a desire to be close to schools and work, high aesthetic quality, and similarity amongst neighbours; $\gamma_{i(x,y)}$ is the location value for factor i; α_{ir} is the preference weight agent r has for factor i, which is a scalar product of the corresponding factor score.

To represent bounded rationality within the model, new residential household agents evaluate their expected utility from only a subset of all available settlement locations. From this subset, an agent settles at a location that maximizes its utility, as described above. The utility approach is useful as it allows agents to combine different types of drivers that cannot be translated easily to a common metric for comparison (e.g. money).

(iii) *Learning and adaptation*

AI and machine learning algorithms provide the ability for agents to retain knowledge, change their behaviour and thus learn and adapt over the course of a model run. For example, Reschke [35] examines the use of genetic algorithms, genetic programming and neural networks, amongst other methods, to represent agent cognition. As well as allowing agents to learn and adapt over the course of a simulation, a further advantage of these models is that they can be trained on existing data to provide highly predictive outcomes.

An example of the implementation of an evolutionary process to represent agent decision-making is provided by Manson [46] in a model of land-use and land-cover change in the southern Yucatan peninsular region of Mexico. In this model, the agents apply a genetic programming, decision-making algorithm to determine the allocation of various land uses. Results conform to various facets of land-use theory that predict the impacts of population on the spatial configuration of agricultural and forest lands and similarly the role of biophysical characteristics and landform on land-use choices. The difficulty in using AI algorithms to represent agent decision-making occurs when mapping the formulated algorithms or rules back to real-world behaviour or processes. Many of these processes can be opaque—'black boxes'—which do not give insight into the behaviour that is being modelled.

(c) ***Creating agent typologies***

Typologies are useful in simplifying SESs where there are very many actors. The creation of agent typologies generally follows one of two strategies: inductive analysis (clustering, participatory approaches) or deductive reasoning (based on theory or expert opinion). In inductive analysis, the use of national social surveys and statistical databases of broad socio-economic characteristics of the population is potentially useful in defining typologies of individuals or households and their decisional rules using factor analysis and clustering (e.g. [47]). However, collecting primary data through a targeted social survey is also an important, inductive approach. Typologies based on a deductive approach using cultural theory and plural rationality have led to agent categories such as fatalist, hierarchical, individual, egalitarian and hermit [48].

The dimensions along which agent typologies can be defined are many, but typically for SES models three dimensions are used. The first dimension describes the functional role of the agents, i.e. the real-world 'actors' to which they correspond. Typically, these agent types are used to represent residential households, farmers, developers, municipal actors (government institutions) or park managers. The roles can correspond to a single individual, a household, or an organization, institution, or other collection of individuals. The second and third dimensions are typically nested within the first so that within a functional role (e.g. farming household), there is a subset of agent types.

The second dimension describes the agent type based on a series of preference weights that are used to define the desires of the agents and guide their decision-making. In most cases, all agents within this functional role have the same decision-making structure, but subtypes are defined by groups of agents with similar preferences (e.g. farmers who value economic outcomes more than environmental impact) that yield similar behaviours and actions within the modelled SES.

An example of defining agent types based on preference similarity is provided by the SOME model described in §3*b*(ii), whereby residential location preferences were empirically grounded using a social survey [43]. A cluster analysis on the factor scores derived from survey responses yielded seven clusters of respondents who shared similar factor scores for distance to schools and work, neighbourhood aesthetics, neighbourhood similarity and household aesthetics, than amongst clusters [28]. These data were used to populate the proportion of residential agent types within the SOME model as well as to define their preferences for the three factors driving residential settlement decisions.

Statistical techniques for clustering and grouping survey respondent preferences are sometimes unable to identify structure, and respondent characteristics cannot be used to predict preferences [29]. In these cases, an alternative to the preference-based typology is required to represent each agent as a unique entity within the space of possible agent preferences. Such an approach could explore the consequence of different agent preference distributions by leveraging the model and systematically exploring the impacts of different preference structures amongst the population or groups of agents within the population. In data-rich situations, where the survey sample is representative of the population of actors, this approach fully embraces the one-to-one mapping capabilities of agents-to-actors and harnesses a high degree of agent heterogeneity.

The third dimension of agent typologies is based on the behavioural mechanisms that the agents use to fulfil their goals and desires (i.e. preferences). Typically, this involves classifying agents into types based on their decision-making process or cognitive strategy. For example, a type of agent may be defined based on the form of a utility function that is used by the agents to make decisions (e.g. risk averse or risk-taking [49]). Similarly, decisions may be made in relation to other agents' behaviours (e.g. repetition, deliberation, imitation and social comparison [50]). The benefit of working inductively within previously defined behavioural theories is that relatively general rules governing behaviour can be created.

The typological assignment from social-survey interview transcripts is itself a useful output allowing a detailed picture to be built up of the reasoning behind decision processes. Where this has occurred in SES research, it is used in combination with behavioural economics experiments (e.g. [51]). In the context of model creation, this third dimension of agent typologies provides empirical support that the theoretical models of behaviour used by the agents and clustered to create the typology are relevant to modelling human behaviour. However, in order to orient the model towards case study use, it should be possible to represent the needs and desires of individuals in a more continuous space, to create a multi-dimensional preference space and to allow a complementary, deductive approach to understanding the behaviour of decision-makers.

Many ABMs tend to focus on either the second or third aspect of this analysis; for example, Brown & Robinson [43] and Fontaine & Rounsevell [47] use the same decision-making mechanism for all agents while varying the preferences—they use a constant decision-making strategy in a multi-dimensional preference space. On the other hand, Jaeger *et al.* [50] use a range of different decision-making strategies with a uni-dimensional preference space.

The use of typologies in the evolution of dynamic vegetation models (DVMs) represents an interesting precedent for the development of ABM. Many DVMs were derived from landscape scale forest gap models [52], but have since been developed for application at global scale levels (e.g. Lund–Potsdam–Jenna-General EcoSystem Simulator (LPJ-GUESS) [53], Lund–Potsdam–Jenna-managed land (LPJ-mL) [54]). The primary principle that has guided this model generalization is the use of plant functional types (PFTs) to represent the attributes of generic plant organisms.

PFTs are primarily delineated by their carbon fixation functions, which are common amongst certain types of plants and differ between others (e.g. C3 and C4 grasses). However, leaf type (i.e. broad or needle), habit (i.e. tree, herbaceous or grass) and other growth processes and characteristics (i.e. phenological processes, rooting depth, and temperature and light tolerances) are also used to define the PFT. Similar to the earlier mentioned typology discussion, it is difficult to generalize a plant along a single typological dimension. The 'function' in PFTs is a combination of dimensions describing how the plant is able to extract resources, out-compete other organisms and carry on its livelihood (photosynthesis). In the LPJ-GUESS DVM, a collection of PFTs comprise leaf type (i.e. broad leaved or needle leaved), phenology (i.e. evergreen or summer green), plant habit (tree, herbaceous, grass) and climate zone (i.e. tropical, temperate, boreal). Other DVMs represent a similar combination of plant characteristics and processes to derive a set of generalized plant, biome or ecosystem types (e.g. BIOME-BGC [55]).

It is plausible that the approach to PFTs could guide, through analogy, the definition of generic human functional types (HFTs) that achieve the same outcomes for ABM as PFTs did for DVMs. HFTs should account for: (i) the functional role of an agent, e.g. a farmer, forester, resident and its functional traits (attributes), (ii) the preferences that represent the agent desires, (iii) the decision-making strategy and behavioural actions and responses and, possibly, (iv) the geographical niches (locations) that they occupy. This perspective is directly analogous to the resource-constrained niches of PFTs in which certain functional types are best adapted to the characteristics of a location and come to dominate at a given moment in time.

In the case of PFTs, dominance is determined by the availability of resources (water, light, nutrients) and the PFT traits. For HFTs, physical resources are important (e.g. the productive potential of land due to soils and water), but resource availability should also refer to access to markets, labour and capital, reflecting the comparative advantage of some locations over others. Such access may be moderated by the political and policy situation (e.g. trade barriers and preferences) or physical infrastructure (e.g. transport networks). In addition to functional roles, however, HFTs need to account for the diversity in human behaviour, and the parallels here with the PFT approach are less convincing. Whether landscape scale level classifications of behavioural types are applicable at global scale levels is a moot point.

The behavioural traits of HFTs might be created from latitudinal case study results that compare similarities and differences in agent types across different landscapes, or they could be created from analyses of national scale statistical databases (e.g. [47]). It is likely also that initial HFT formulations would follow more deductive, expert-opinion-based approaches. However, the availability of unified databases of human behavioural traits across the globe would be invaluable in allowing the variation in behavioural types and attributes to be determined inductively. Similar exercises exist for the establishment of global PFT trait databases [56].

(d) *Agent population*

The population of agents can change over time or remain static. In most representations of SES, the agent population changes over time. In the case of modelling human populations or households, most SES research uses census or housing survey data to derive historical trends and future trajectories of population and households. These data are then interpreted to define the rate of agent creation or removal from models. In some instances, these survey data are used to create initial population conditions that are extended through demographic processes to create endogenous growth or decline via birth, death, immigration and emigration (e.g. [47]). In both cases, the system is not considered to be closed since exogenous factors (e.g. immigration) contribute to the rate of population growth.

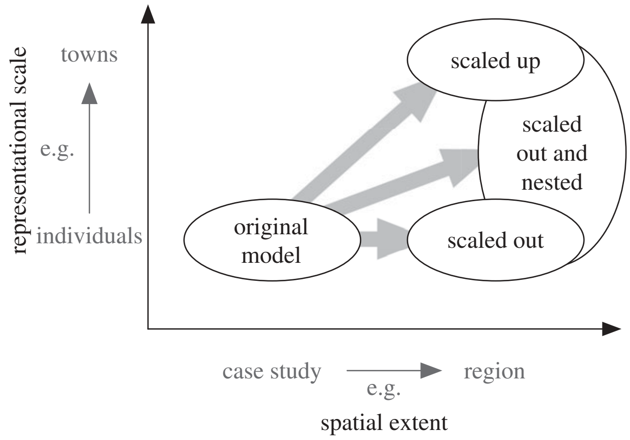

Figure 4. Graphical representation of scaling out, scaling up and nesting.

When ABMs of SES are considered to be closed systems, the agent population may be fixed. Land-use models that include land markets often use a fixed agent approach to address research questions associated with market clearing and the resulting spatial patterns of land rent (i.e. house prices, land price gradients, etc.), e.g. [57]. In these cases, census data are coupled with housing survey data to provide better estimates of the number of households and housing units, e.g. [58]. However, these data sources are inadequate when empirically grounding the characteristics of the agents and the market such as the asking, bid and sale price or the willingness to pay or accept prices.

4. SCALING

Because of the need to collect primary empirical data about agent attributes and behavioural rules, previous ABM applications have typically been carried out at the case study or landscape scale. The transition to ABM applications over larger geographical regions will require advancements in knowledge, methodology and technology. There are, however, pressing reasons to support the application of ABMs over larger geographical regions, not least to facilitate the integration of agent-based models with ecosystem and vegetation models at different scale levels. The application of ABMs across large geographical regions would also provide the means of generating model outputs at a scale level that is relevant to a range of policy processes and political jurisdictions. Here, we discuss the ways in which ABM could be generalized for applications over larger geographical extents, in order to propose suitable ways forward for SES modelling based on agent-based approaches. There are three basic methods to change the scale of model applications (figure 4):

- scaling out: applying the same model across a larger spatial extent by increasing the extent of the input data;
- scaling up: aggregating model behaviour to a higher representational level, such that former entities are represented as groups; and
- nesting (multi-model approach): representing higher level processes as aggregate models that

influence agent behaviour at lower scale levels, e.g. institutions that monitor agent practice or ecosystem function can change the constraints, incentives or rules that influence agent behaviour.

(a) *Scaling out*

In scaling out, the approach is to use fundamentally the same model, but to increase the extent of the data baseline from a small to large geographical area [59]. This has the advantage that the basic model functionality does not change, so there is no need to build new algorithms into the model since these do not change when scaling out an existing agent-based model. In applying this approach, however, the quantity of input data increases greatly, which may be limited by data availability. With more data, computer processing time also increases greatly and, therefore, scaling out approaches are likely to require high-performance or massively parallel computing [60]. The approach also assumes that the processes being represented are as relevant to the larger area as to the original area within which the model was developed, which in practice may be beyond the calibration range of the model.

To date, only a handful of ABMs could be considered to have been scaled-out. The transportation analysis and simulation system (TRANSIMS) agent-based model was developed over 9 years at Los Alamos National Laboratory. TRANSIMS models the activity patterns of individuals within a city and models city-wide traffic flows and behaviour that result from the individual agent decisions [61]. The model was later extended to address epidemiology research questions by modelling 1.6 million people in Portland, Oregon (epidemiological simulation system; EPISIMS). Both models relied on census data to create an agent population with similar demographics. Additionally, a survey was conducted with thousands of households to obtain information about daily activity patterns, which were used to construct activity patterns for the agent population [61].

The ability to scale out ABMs by researchers without access to super computers is increasing with the development and increased use of general purpose graphic processing units (GPGPUs). Lysenko & D'Souza [62] implement the well-known Sugarscape agent-based model by Axtell and Epstein [63] in a GPGPU framework that modelled over 2 million agents and ran at a speed significantly quicker than traditional ABM tools (e.g. Repast Simphony) that are run on central processing units and do not execute agent behaviours in parallel. Although the use of GPGPUs, parallel programming and high-performance computers provides a way of scaling out ABMs of SESs, these approaches typically require modification to, or different, conceptual models that conflict with object-oriented programming concepts that are the foundation of ABM (see [62] for more details).

(b) *Scaling up*

We define the scaling up of an agent-based model as changing the entities represented so that individuals become aggregated, i.e. reducing the representational granularity to allow a larger spatial extent to be covered. As a hypothetical example, an agent-based model may be used to evaluate how policy changes the dynamics of land competition in an SES among different actors (e.g. farmers, developers, residents, businesses). When scaled up, the agents would be municipalities, counties or states, and the model would be used to explore how land demand, supply and quantities of land-use and land-cover change over time across a larger spatial extent. A key issue is how far it is possible to apply the mechanisms used at one scale to a larger scale—for example, can competition between municipalities be modelled in the same manner as between individuals—and how much do new processes need to be modelled, for example drawing on political science.

Political scientists have been applying ABM at national and state levels to investigate national boundary formation [64], regime change [65], inter-state conflict [66] and voting behaviour. The approaches to using survey data by political scientists and the types of interactions they are interested in may aid our understanding of how to scale up models of SESs. Typically, we are interested in scaling up instead of scaling out because we do not have data at the fine resolution of individual actors across the larger geographical extent of desired application: even when data exist, acquisition may be too costly or too difficult. Similarly, the researcher may be time constrained or not interested in specific micro-level interactions and outcomes (e.g. precise location of land-use change). Under these circumstances, scaling up an agent-based model would be preferred to scaling out, as coarse-grained data are easier to obtain and work with.

(c) *Nesting*

A nesting approach to ABM involves using feedbacks and interactions between agents or processes that act at different spatial or temporal scales. Typically, case-study-based applications of ABMs treat policy and the institutions responsible for these policies as exogenous. Policy evaluation is typically undertaken by imposing *ex ante* scenarios of alternative policy options. However, as one scales-up and -out from detailed (and small) case study areas to wider geographical extents, system boundaries shift to such an extent that the governance structures reflected in institutions become a component part of the system itself. Consequently, there are feedbacks associated with strategic policy implementation. As policy institutions observe or perceive a problem or lack of performance within an SES, they intervene through regulations or incentives that seek to mitigate the problem by influencing actor behaviour. Through such feedbacks, institutions become endogenized within an SES. This raises interesting questions about the need to incorporate the representation of governance processes and even institutional emergence in SES models.

ABM has the potential to play a much larger role in integrating science and policy and, as a result, have a larger impact by reaching a broader audience (of both basic science research and decision-makers). Institutions as organizations can be represented as agents with the heterogeneous agent attributes, a unique goal-orientation, and rule-driven behaviours and interactions with other agents and their environment.

Again, typologies would be useful in understanding the types of roles, preferences and behaviours of institutions and organizations, and how they affect, and are affected by, SESs. A large number of individual agents at lower scale levels could be nested within an SES with a limited number of institutional agents operating at a higher scale level. The institutional agents observe the landscape that changes in response to the actions of individual agents and respond accordingly through policy implementation.

This type of modelling strategy could lead to a number of simulation experiments that explore the role of different governance and institutional structures and processes in determining SES responses to environmental change. One might assume that policy intervention would mitigate many of the environmental change problems faced by SESs, but this could be tested experimentally with such models. It would also provide an opportunity to explore how individual agents fare under different governance regimes, and what would be the consequences for their behaviour. This could assist in the design of more effective governance structures and policy options.

5. DISCUSSION AND CONCLUSIONS

The use of ABM to address SES research questions provides a unique opportunity for scientists and practitioners to represent a range of interacting human and environment processes that act out at different scales. To fully use ABM as an approach to scientific enquiry requires the identification of the actors who drive SES changes in the real world and map them onto agents in models. This mapping process is not straightforward since it involves data collection beyond the typical household characteristics found in census data. While these data are useful, targeted social surveys are necessary to record actor preferences, behaviours and how they make decisions. This often requires an iterative modelling process that collects data and information over time, while systematically incorporating those developments into an agent-based model. Using this type of iterative modelling process changes the agent-based model from an application tool to an approach for scientific enquiry that: (i) acts as a medium for discussion amongst interdisciplinary research teams and stakeholders, (ii) formalizes assumptions about the way SESs behave, (iii) acts as a repository for data, findings and information, and (iv) provides a computational laboratory to experiment with policies and actions that aim to change the SES in a particular way.

Most new data collection will involve socio-economic variables since these data are most commonly lacking. A number of methods exist for the collection and analysis of new socio-economic data based on the principles of social survey. This might include the use of interviews, questionnaires or other semi-quantitative elicitation methods such as conjoint analysis [67]. The principle that underpins the use of these methods in ABM development is to understand the rules that determine agent behaviour and preferences and how this underpins decision-making as well as to create typologies that seek to simplify agent representation where a system comprises many actors.

While the focus of this paper has been on mapping actors to agents using data from social surveys, scaling ABMs is probably the best approach to map back from agents to actors. By scaling out and scaling up, ABMs become more useful in addressing changes in the provision of ecosystem services across SESs. This involves linking ABMs to ecosystem process models such as LPJ-GUESS and BIOME-BGC to provide estimates of ecosystem function [68].

There are many intellectual problems that need to be resolved in scaling out and scaling up ABM applications from landscapes to nations and beyond, but the use of typologies to simplify the modelled system is likely to be crucial. We argue that typologies play a crucial role in scaling out, scaling up or nesting ABMs because: (i) it is necessary to generalize and simplify complex SESs to gain understanding, (ii) the data requirements for high-fidelity simulations of detailed SESs are enormous, and (iii) modelled SESs are not deterministic and incorporating stochastic elements requires a number of model runs to create an envelope around potential SES outcomes. As a result, there is a need to derive generalized representations of the actors in SESs across multiple dimensions of role, preference and behaviour, and this is the basis of HFTs.

The concept of PFTs and HFTs may also be applied to the notion of higher representational units such as institutions in order to derive a set of institutional functional types (IFTs). Institutional agents would need, however, to be coupled with individual agents, such as land managers or ecosystem beneficiaries, and this is the role for a nested-scaling approach.

We conclude this paper with a number of key points about further development in ABM techniques as a means of improving the assessment of change in SESs:

- a number of approaches exist to represent human behavioural and decisional processes in SES models, although little is known about how these different approaches compare across different contexts;
- the capacity for ABM to generalize the knowledge of SES processes and mechanisms that act at the local level and to apply this to large geographical regions represents a crucial next step in modelling SESs, although this comes with considerable intellectual challenges;
- the development of thinking around the notion of HFTs, as an analogy of PFTs, would allow ABMs to be scaled to larger geographical extents; and
- the representation of institutional agents in SES models would allow a number of important research questions to be tackled that relate to the role of governance structures and policy formulation in determining SES change.

The authors acknowledge inputs to this paper derived from a number of funded research projects: the MISTRA-SWECIA project (*SWEdish research programme on Climate, Impacts and Adaptation*), the Knowledge for Climate CARE project (*Climate Adaptation for Rural arEas*) and the European Commission funded projects, Ecochange (*Challenges in assessing and forecasting biodiversity and ecosystem changes in Europe*; FP6-036866), Plurel (*Peri-urban land-use* *relationships—strategies and sustainability assessment tools for urban-rural linkages*; FP6-036921) and Volante (*Visions Of LANd use Transitions in Europe*; FP7-265104). The authors also thank Ben Smith, Martin Sykes and Almut Arneth of Lund University and Martha Bakker of Wageningen University for their insightful comments during the preparation of this paper.

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