Using Agent-based modelling to simulate Social-Ecological Systems across scales

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Abstract

Agent-based modelling (ABM) simulates Social-Ecological-Systems (SESs) based on the decision-making and actions of individual actors or actor groups, their interactions with each other, and with ecosystems. Many ABM studies have focused at the scale of villages, rural landscapes, towns or cities. When considering a geographical, spatially-explicit domain, current ABM architecture is generally not easily translatable to a regional or global context, nor does it acknowledge SESs interactions across scales sufficiently; the model extent is usually determined by pragmatic considerations, which may well cut across dynamical boundaries. With a few exceptions, the internal structure of governments isnot included when representing them as agents. This is partly due to the lack of theory about how to represent such as actors, and because they are not static over the time-scales typical for social changes to have significant effects. Moreover, the relevant scale of analysis is often not known *a priori*, being dynamically determined, and may itself vary with time and circumstances. There is a need for ABM to cross the gap between micro-scale actors and larger-scale environmental, infrastructural and political systems in a way that allows realistic spatial and temporal phenomena to emerge; this is vital for models to be useful for policy analysis in an era when global crises can be triggered by small numbers of micro-level actors. We aim with this *thought-piece* to suggest conceptual avenues for implementing ABM to simulate SESs across scales, and for using big data from social surveys, remote sensing or other sources for this purpose.

Keywords: Agent-based modelling, Social-Ecological Systems, cross-scale, ABM, SESs

1. Introduction

The social-ecological systems (SESs) concept describes the tight coupling of human and environmental systems that mutually influence each other [1-4]. An SES in this view includes the ecological components of an interdependent group of organisms or biological entities, within a bio-geophysical environment [5-6]; and a social component including the actors whose activities directly influence ecosystems and those that govern human-nature interactions which can be the same or different actors. Resulting interactions are mediated by the broader social, economic, and political settings and the larger ecosystems within which the SES is embedded [7]. Interactions are continuously changing due to feedbacks and internal or external factors, taking place across different temporal and spatial scales, making SESs highly dynamic systems [8-10].

Agent-based modelling (ABM) has become a well-established computational approach for studying SESs [11-14]. Many ABM examples have focused on simulating case studies at the level of villages, rural landscapes, towns or cities [e.g. 12, 15-17]. However, ABM architecture that focussed on case studies is not easily translatable to a regional or global context, nor does it acknowledge SESs' interactions across temporal and spatial scales sufficiently [4, 18, 19]. Even within a single domain, such as ecosystem dynamics or economics, models must deal with cross-scale interactions; for example, models of infectious disease transmission may need to integrate processes at cellular, host and population level [20]. In economics, conventional models, which ignore agent heterogeneity and cross-scale interactions, cannot capture such phenomena as the default of a single firm triggering a macroeconomic bankruptcy avalanche [21, 22]. Moreover, international trade may show both fast and slow dynamics through coupling between political agreements, international markets, supranational bodies such as the World Trade Organisation, and biophysical processes that affect crop growth or the availability of fuel. With the growing active use of ABM in policy, national disaster planning and even global poverty analyses by the World Bank [23], it is timely to consider how scale issues might affect the usefulness and validity of model results. The main challenge for modelling SESs across scales is that the most relevant scales may themselves vary temporally depending on the system's dynamics. Near a tipping point or phase change, small fluctuations in some parts of the system may propagate to affect the whole [e.g. 24], whereas at other times, change might remain spatially or temporally localised - a point that is generally true for many kinds of dynamical systems.

In this *thought-piece* we discuss conceptual avenues for using ABM to simulate SESs across scales. The growing availability of *Big Data* such as social panel surveys, earth observation systems, and other available sources may help, but their partiality and bias could pose difficulties. Understanding the roles of multiple stakeholders such as political actors, resource users, citizens or agencies who may have direct or indirect influences and interest in decision making is integral for understanding SESs across scale. The core proposition is that in a world that is increasingly connected and multi-scale, solutions that support policy design and decision making must be as well. We aim to contribute to the ongoing debate on appropriate approaches for ABM to upscale dynamics emerging from lower level interactions to SESs representing larger geographical areas and the relevant high-level social structures and institutions [4, 16, 19, 25, 26].

In the remainder of this paper, section 2 sets the scene and introduces approaches for representing human behaviour across scales with a particular focus on economics, behaviour, and governance systems. Section 3 discusses fundamental aspects of using ABM to simulate SESs across scales, e.g. scaling mechanisms, parameterisation and uncertainty assessment. Section 4 then examines in more detail some specific conceptual and methodological directions, and section 5 concludes the paper with an outlook on key next development steps.

2. Theoretical considerations and conceptual challenges

Scale is a complex issue: spatial scale in particular has been the subject of considerable technical development in its analysis [27, 28] and of theoretical debate, with some authors even suggesting banishing the term [29], although in practice their main point is that the dynamics of scale are complex. In particular, it is important to distinguish the scale of analysis from that of processes [30], the danger being that pre-selection of a given spatial unit might prove to be inappropriate for the underlying dynamical system.

Gibson et al. [31] and Cash et al. [32] have surveyed the cross-scale issue in the light of global environmental change and governance structures and define scaleas "the spatial, temporal, quantitative, or analytical dimensions to measure and study any phenomenon", and levelsas "the units of analysis that are located at different positions on a scale" [32].Assuming that scale implies some sort of hierarchy of organisation, e.g. forms of jurisdiction from village to country, *cross-scale* then refers to interactions between different levels in the hierarchy, whereas referring to *cross-size* could include horizontal interactions between two entities of different sizes. Interactions may occur within or across scales, leading to substantial complexity in dynamics, and change in strength and direction over time. For example, decentralization reforms can produce periods of strong interaction among national institutions and local governments during struggles involving power, responsibilities, and accountability but then settle into a much more modest and steady degree of interaction [33, 34]. Understanding the dynamics of SESs across scales is crucial to support policy design and the sustainable management of natural resources, because it reveals insights into processes in both socio-economic and environmental subsystems and the feedbacks between them [8, 16].

SESs modellers, however, need to distinguish between, and deal simultaneously with spatial, temporal and social scale. For example, modelling a small isolated region for many years without considering possible cross-scale interactions is likely to lead to substantial error in future projections; while there may be fast financial dynamics, for other processes (e.g. access to resources of population migration) situations at greater spatial distance will typically tend to increase in importance as the simulation time is increased; social scale has both spatial and temporal aspects, but cannot be reduced to either. People in the modern world typically belong to many social formations, from households and friendship networks to cultures, polities and worldwide economic systems; and there is no simple relation between the number of members and their geographical spread or temporal endurance. Spatial, temporal and spatio-temporal entities all form *tangled hierarchies* [35], in which one entity may be a part of several larger entities which overlap each other, particularly when we consider multiple domains: for example, the boundaries of hydrologically, ecologically and politically defined regions rarely coincide. These complexities pose difficulties for the SESs modeller.

2.1 Agent attributes and social interactions

In the social world, organizational scales range from the single individual to all humans, and from small cooperative groups to large multinational organisations.

Various groups of people might be acting in the same space and be independent, in competition, or interdependent at different scales. These relationships between or within groups can be crucial for the dynamics of SESs across scale.

Drawing inferences about the behaviour of individuals based on grouped or area-level data needs to be avoided. On the other hand, individual-level data may not always be available due to commercial or privacy reasons or their partiality across temporal and spatial scales, in which case theory-based assumptions, e.g. about distributions of characteristics among agents of a group, can be used. However, cultural variations that shape norms and values, and which one acquires in youth may never directly reach consciousness [36], so that the drivers of behaviour may not be easy to understand. How much these dynamics need to be incorporated in a given model will depend on model purpose, but the complexities of variation across scale need to be considered. For example, while social networks are commonplace in many agent models, people will typically belong to multiple networks with different physical and social reach. The interaction between these networks is likely to be of as much importance for some phenomena as the networks on their own (e.g. see also Section 2.3 below).

The anthropocentric nature of the ecosystem service concept has further re-focused attention in ecosystem analysis from the ecology of *nature* to the important influence of people on the environment and the role of ecosystems in supporting human wellbeing [12, 37]. Frameworks for agent-based SESs models increasingly seek to address the characteristics of people and their dynamic interactions with the environment, e.g. MoHuB (Modelling Human Behavior) [38]. A recent review by Groeneveld et al. [16] showed that the majority of human-decision making models focused on land use change were not explicitly based on theory. But in order to make use of the full potential of ABMs across scales in understanding global change, model purpose must drive design choices, specifically the modelling of human decision making and social interaction. Where rich understanding is the purpose, full use needs to be made of theories from sociology and cultural psychology [39] and any discipline offering a plausible or structurally valid description of the issue under study. It is particularly relevant to have a realistic representation of human decision making when one is interested in future scenarios as this can significantly affect model outcomes.

2.2 Economic structure and interactions

Many authors [e.g. 4, 40, 41] recognize that classical multivariate statistics and general equilibrium approaches cannot capture the dynamics of SESs. Mainstream macroeconomic theory, however, remains rooted in general equilibrium micro-foundations, with utility maximizing households and profit maximizing companies. Equilibrium is reached by external imposition of conditions requiring fulfilled expectations and market clearing [42]. The representative agent framework is used to provide micro-foundation for aggregate behavior, in a setting in which equilibria are unique and stable. Several studies, starting from Sonnenschein [43] and Debreu [44] show that such conditions do not exist, so the representative agent is actually not representing anyone [45]. In the social simulation literature, similar critiques are already accepted [46].

Agent-based computational economics [47, 48] aims to go beyond the behavioural assumptions of neoclassical economics and consider both agent-agent and agent-environment interactions. Equilibrium conditions, homogeneity, or other external coordination devices, which have no real-world referents need not be imposed [49]. Interactions are not centralized but related to some concept of proximity, which can be geographical but also behavioral or cultural among other possibilities. Interaction among agents, with balance sheet constraints at the individual level, allows for a rich out-of-equilibrium dynamics. Endogenously-generated dynamics can then produce growth and business cycles [50].

ABMs are able to replicate empirical features at many levels. One can check features at the aggregate level (i.e. GDP, inflation, systemic risk), or at the micro level studying the evolution of single agents, or in distributions (e.g. firm sizes), comparing them with corresponding distributions from real economies [51]. In the field of climate change, Farmer et al. [52] declare the need for a third wave in the economics of integrated assessment modelling, examine the potential of dynamic stochastic general equilibrium models (DSGE) versus ABM, and point out the huge potential of ABM in particular for estimating damage functions and scenario analysis. Indeed agent-based analyses suggest climate damage may be greater than standard integrated assessment models [53]. However, the complexities of generating well validated ABMs could make policy makers at central banks rather sceptical about fitting ABM macro models to data, instead of using standard reduced-form models. Thus, policy makers might turn to ABMs primarily when trying to study economic propagation mechanisms in a controlled experimental setting. In particular, simulating the economy in extreme situations, such as financial crashes, where standard models have failed [49], or in assessing the effects of poverty, where measures such as GDP may miss the plight of the poor [23].

2.3 Governments and Governance systems

With a few exceptions [e.g. 54, 55], governments are simulated by agent-based models as single agents without the consideration of internal structure. The representation of institutional and governance structures of SESs across organizational entities however is crucial in understanding the ways in which organizations and policy provide feedbacks to individual agent behaviour. Agent-based interactions are affected by an interplay between stakeholders and institutions at multiple scales and across scales [32]. Adequately representing human decision-making across scaleswill be an important prerequisite for future ABM in order to serve as tools for policy making and avoid unintended consequences [56, 57]. Attempts at modelling human decision making [38] have tended to concentrate on the behaviour of individuals' in households, businesses or agricultural systems. Other approachessee also [4, 9, 12, 13, 14]use'what-if' scenariosto evaluate the potential impact of future policy options on SESs *vis-a-vis* in using ABM to assess policies in retro perspective with the drawback ofnot allowing for feedbacks between modelling outcomes and policies. In other cases,the prospective impact of a certain policyis assessedby comparing simulation resultsof selectedoutput parameters or the behaviour of one or several subsystems [11, 22,51].However, some examples of models that simulate behaviours of governments and international organisations are available [58-63], and may take into account various hierarchies (typically citizens/ businesses at one level and governments above, or political parties and the media [64]).

Local decision-making processes can have spillover effects and can influence dynamics at different scales. Conversely, different types of actors at regional, national or international scale influence individual livelihoods or localized ecosystems through institutions or market dynamics. Brondizio et al. [65] argued that governance of SESs requires social institutions that link multiple scales in order to be effective [see also: 66, 67]. Usually government action emerges from a complex set of interactions between state and non-state actors with differing roles (e.g. politicians versus civil servants) divided and conflicting interests and loyalties (e.g. conformity to party line versus personal advancement), formal and informal processes (committee structures versus informal alliances, lobbying), legal and regulatory frameworks, fiscal and financial pressures and influences from media and the public. These interact with wider actors that constitute the governance system (NGOs, public service organisations, municipalities, security forces, local communities etc.) in sets of overlapping self-organising structures.

Current models thus fail to exploit the full potential of ABMs to represent governance, where collective behaviours and informal institutions are generated endogenously through the interaction of individual agents within institutional and biophysical environments. This results partly from a focus on a single scale (often the local village, town or region) but also from the high complexity involved in the interactions between the many actors involved and the nature of decisions and processes that define and characterise them. It is in fact often difficult to identify who is actually involved in the decision-making process and therefore whose behaviours should be captured. This complexity can make it difficult to decide for a given model purpose which actors and dynamics need to be modelled and which do not.Such decisions should therefore always be guided by the research question and model purpose which drives the choice what is included in a model.

2.4 Ecosystem structure and processes

Biophysical structures and processes have previously been integrated in ABM using a variety of approaches, depending on the research question, model purpose, data availability and the trade-off between model complexity and its expected payoff. In ecology, the IBM acronym (Individual Based Model) is preferred to ABM [68]. A range of cases is reviewed by Luus et al. [69], including those where the environment is (i) regarded as static [70, 71] assuming that environmental change is much slower than other processes, or insufficiently well-known to model; (ii) treated using statistical regression methods where feedbacks may not be important, or ecosystem measures are simply outputs; or (iii) regarded as if in equilibrium (e.g.

when cast into a General Equilibrium economic framework, [72]). Other cases include the modelling of an aggregate stock that changes dynamically through harvesting and population growth [73], or hybrid models that represent the biophysical side using an equation-based approach [74].
Dynamical models may also be dealt with using transition rules [75] if ecosystems are not the main model focus, or are not changing in character in response to human activity; or with stock and flow (system dynamics) type calculations [76] or more general flow calculations to look at ecosystem service provision [77]. However, more relevant for the current purposes is the combination of ABM with IBM [78, 79], as IBMs have been argued to be a necessity for next-generation ecosystem models to capture the complexity of ecosystem dynamics [68]. The most complex type of models in this regard are Earth System Models (ESM), incorporating Earth's atmosphere, cryosphere, oceans and lands on a global scale [80]. To date, ecosystem dynamics in ESM have been limited to vegetation on the land surface and plankton-based biogeochemistry in the oceans, representing only the net primary productivity from photosynthesis. Rounsevell et al. [18] highlight the possibilities of integrating ABMs with ecosystem and vegetation models over larger geographical areas. More recent work has pointed out the need for such global models to be process-based and to include animals and marine ecosystems [81, 82]. At least one global scale treatment of coupled animal and vegetative ecosystems on land and in the ocean has now been created [83]. However, the general vision for development of these models still lacks representation of human agency, decision making and adaptation [25], and the focus remains on climate change rather than other anthropogenic-driven factors that affect ecosystems [84].

2.5 Infrastructure and Socio-Technical Systems

Gotts and Polhill [35] propose extending approaches of SESs to socio-*techno*-ecosystems, pointing out that human artefacts influence the interactions between people and the natural environment (the socio- and -ecosystem components of an SES) in both intended and unintended ways, and that this influence has grown increasingly important over historical time. In particular, technological change has not only permitted and encouraged the long-term increase in human populations, it has also, particularly through the construction and maintenance of large-scale infrastructure such as road and rail systems, ports and airports, wired and wireless signal networks, radically altered the topology of the interaction networks among individuals, social groups, and ecosystems, by facilitating travel, goods transport and the accompanying transport of non-human organisms, both intended and unintended, and communication. At present the study of SESs and of socio-technical systems [85] are both recognised areas of study, but given the significant impact of human structures on ecosystem degradation as for example represented by roads opening up forested areas [86], we argue for a unification of the two areas. Whether or not we adopt new terminology such as *socio-ecological-technical systems* (SETSs), this points to one of the ways in which the concept of a SES, and consequently, SESs model design, needs to be re-examined and extended to deal with cross-scale dynamics.

3. Agent-based modelling for SESs across scale

3.1 Model design

To model SESs across scales adequately, modellers must deal with the dynamics of all the five aspects of these complex systems described in Section 2: human agency including social norms and culture, economic structures and processes, governance, ecosystem dynamics, and technology. All occur at multiple scales, and there is constant interaction not only within the same scale, but also across different scales. There are two main approaches in designing cross-scale agent-based models: building one complex model or the coupling of already existing domain-specific submodels as for example discussed by Verburg et al. [4] or Millington et al. [87]. In the first case, modular frameworks have been developed to facilitate modification and reuse of model components as for exampleshown with NetLogo (http://ccl.northwestern.edu/rp/levelspace/), wholeSEM (http://www.wholesem.ac.uk/research-models/linkages) or byGilbert et al. [67] While the modular approach takes advantage of already recognized disciplinary submodels, there are real challenges with regard to the matching of scales and spatial resolutions, and progress is often hindered by disciplinary jargon and implicit assumptions as well as the way uncertainties within components propagate throughout the whole model [19]. Parker et al. [88], discussing agent-based land use modelling, outline three possible modes of linking the natural and social components of such models:

- Natural science models as inputs to social systems models, with no reciprocal linkage.
- Natural-social-natural linkage in a one-way chain, where the natural systems modelled as providing inputs to and accepting outputs from the social system may be different (e.g. a crop growth model affecting modelled land use decisions, which in turn affect modelled wildlife).
- Endogenous determination of common variables through interactions between natural and social system models.

In agriculture, linking models of disease spread and mitigation procedures is accepted practice, as e.g. in the work of [89]that integrates a simplified individual-level model of the spread of potato late blight *(Phytophtora infestans)*, in a landscape-level model of farmer's crop choice and management. First, the natural system was modelled. Then, farmer practices were added, both in the model and in interactive sessions with farmers [90]. Similarly in [78] an individual ecosystem model for tree growth provided a dynamic landscape for farmers to both harvest trees and clear land for crop growth. The modification of the soil permeability then fed a hydrological model for simulation of the subsequent change in the profile of flooding. Coupling of these models was achieved through access to the source code for each sub-model and re-writing them to form a common framework in which the space and timescales could be matched to the smallest appropriate for the whole model set. However, feedbacks from the environmental modification into farmer behaviour or forest dynamics from the altered pattern of flooding, and the potential effects of this downstream of the model catchment, either in terms of other residents, or on policy for forest conservation or flood management were not accounted for, despite a nominal model run time of hundreds of years.

The implication we draw is that the last of thethree modes discussed above is really a requirement rather than an option: since the systems modelled are complex and the relative importance of dynamical aspects are unknown ahead of time, predetermining the direction of interactions could lead to expensive mistakes if applied to policy.

In all cases, models must be linked *via* common variables, representing hypothesized causal connections between the natural and social systems. But the scales at which key processes are best modelled, and at which data is available, may differ between the natural and social domains, and causal connections may be indirect, crossing spatial and temporal scales: for example, the land use decisions of individual farm households may have a noticeable effect on potential pollution problems only in aggregate, so even if these effects react back on farmers, individual farms may not feel these secondary results of their own decisions.

Voinov and Shugart [91] advocate integrating the empirical datasets used for calibration into models with multiple components. When module *A* feeds into module *B*, *A* should first be run using empirically-derived inputs (the “calibrated base run”), and its output compared with empirical data. When run in a different scenario, the output of A should then be modified “by the same increment as the scenario output from module *A* is different from the calibrated base run”, in order to avoid the risk of propagating modelling errors between model components. Of course, this approach assumes the required data are available, which as Parker et al. [88] point out, may not be the case. Whether *Big Data* can come to the rescue here we consider below.

Different terminologies and conceptualizations of the involved domains also hinder the design of an integrated model. ABM requires the expression of concepts in a formal programming language without the residual ambiguities present in the natural language [92]. Therefore, while the integration of domains and scales remains laborious, ABM as a modelling approach provides a basis for such an integration [93]. Polhill and Gotts [94] and Janssen et al. [95] describe the use of formal ontologies to improve the modularity and conceptual transparency of models in the area of agricultural systems. Such ontologies consist of a conceptual hierarchy of classes (generally a *tangled hierarchy* in which a concept may have multiple super-concepts or generalizations), and an associated hierarchy of relations which may hold between members of specified classes. The ontology will typically be constructed using input from domain experts and/or stakeholders(actors whoare relevant because they play a role in and/or are significantly affected by the SES, including decision makers at a specific scale of interaction), so that it acts as an intermediate representation between natural language and computer code, which is frequently opaque to all but the programmer, and generally includes features such as schedulers and displays, which are necessary to make the model work or to assist the user, but are not intended to correspond to anything in the system modelled.

A key aspect here is to be sure to adopt sound principles of software engineering (use of version control, formal repeatable unit testing, continuous integration of software updates and testing, comprehensive documentation, open source code) as the norm for complex model development [96]. Otherwise problems with repeatability of model experiments are likely to persist and potentially become more severe as models are made more complicated. Establishment of trust for policy purposes must thus rest on a foundation of good model testing, built in at design time, although considerable challenges remain where software is built by multiple remote teams [97].

As a further issue, while ABM and IBM in principle allow for the inclusion of all possible dynamical scales down to the level of individuals, and seem ideally suited for integrated modelling of SESs, there are a number of difficulties with ecosystem models that go beyond the issues of commensurability of time and spatial scales that arise when coupling models together, or the issues of model complexity [69]. The sheer number both of species and of individuals leads to problems of coverage, especially as the smaller individuals can be both very numerous and significant in ecosystem change, and we may not have an obvious way to even make assumptions about their behaviour. By comparison, modelling every person on the planet is relatively less computationally difficult [98]. Harfoot et al. [83] adopt a *functional type* solution for animals, and Arneth et al. [25] suggest a similar approach for human agents. This at least allows for an encoding of generic behaviours, but still leaves the issue of agent numbers. An approach to deal with this is to fuse together the more numerous agents into collectives, (sometimes called cohorts, [83]) or super-individuals, although this can lead to some changes in the observed model dynamics [99].

3.2 Parameterisation, sensitivity analysis and validation

The parameterisation of agent attributes and behavioural response functions to represent decision-making processes requires information from qualitative and/or quantitative empirical sources, e.g. expert knowledge, surveys, or interviews [100]. ABMs of SESs further require the incorporation of the biophysical environment resulting from natural processes and human behaviour insofar as it is relevant for the agents' behaviour and to understand feedbacks between human behaviour and environmental processes [101].

Many scholars [e.g. 102, 103] argue that *Big Data* offer new avenues for applications such as ABM. *Big data* refers to the increasingly available and abundant information at a near-continuous timescale that are produced by web-based services, digital earth sources (e.g. satellites, climate stations), cheap field sensors, telecommunication and social networks, or open source applications such as OpenStreetMap. Many of these datasets are spatially and temporally referenced and offer many possibilities for enhancing geographical understanding, as they are directly or indirectly related to geospatial information.A potential drawback of these datasets is their often commercial character making them sometimes not publicly available due to commercial reasons, privacy or national security issues.

Using ABM across-scale to simulate behavioural responses of humans would require two fundamental steps in which empirical data are required: the development of behavioural categories and scaling to the whole population of agents. Smajgl et al. [100] suggests doing this by first characterising the existing heterogeneity of agent attributes and behavioural responses and then providing simplified descriptions of behavioural realities. Arneth et al. [25] discusses agent functional types, analogous to the plant functional types that are used in dynamic vegetation models: agent typologies to represent agent roles, attributes and behaviour in larger populations. With the advent of sufficiently rich data streams and a sufficient behavioural model the possibility of both improving predictions and obtaining parameter estimates continuously over time becomes available. These techniques have been used in weather forecasting models for some time, and allow one to correct model output to bring it closer to observations. Ward et al. [104] shows how such dynamic data assimilation techniques (technically, the Ensemble Kalman Filter) can provide more insights into the system state compared to standard time series or statistical methods. However, they emphasize the need for more efficient parallel-computation to enable the necessary large number of model runs, and a careful sensitivity analysis to ensure that model mechanisms are representing the microscopic dynamics.The software PCRaster (http://pcraster.geo.uu.nl/) can be drawn as an example that allows for dynamic and spatial-explicit modelling of SESs further allowing error propagation techniques such as Monte Carlo or Kalman Filter techniques.

There are a few examples of ABM of SESs where extensive sensitivity analysis has been performed [12]. Often such ABMs focus on scenario comparison where highly aggregated model outputs, e.g. influence of food prices on policy or institutional arrangements is tested [19]. However, ABMs cannot be properly understood without exploring the range of behaviours exhibited under different parameter settings or structural assumptions (e.g. different functional forms of presenting human decision making processes) and the variation of model output measures stemming from both random and parametric variation. Hence, sensitivity analysis needs to emphasise the model's entire range of behaviour, and to determine how sensitive model outputs are to different input variables caused by the (i) nonlinearity of interactions (at a single, multiple or across scale), (ii) non-normality of output distributions, and (iii) strength of higher-order effects and variable interdependence [105]. In contrast to common statistical approaches of sensitivity analysis [e.g. 100], computationally-intensive approaches are just becoming available, e.g. machine learning [106] or Bayesian inference [107] to estimate system states and the marginal likelihood of the parameters. Again, such approaches tend to require many (thousands) of model runs to be effective.

Validation of ABMs that simulate SESs by comparing model results to real-world data or patterns is still in its infancy and is discussed controversially in literature (see: [19] for a review). For example, Polhill et al. [8] argue that validation methods appropriate for ABM could be expert validation or pattern-oriented modelling [108]. Verburg et al. [4] state that agent-based modelling should be used to explain why SESs behave in an observed pattern, either spatially or temporally or as combination of both. Once more, a particular challenge for ABM across scales will be also data availability because information of SESs across scale will be not always available at all scales considered nor for the interactions between different SES subsystems, e.g. actors, governance, ecosystems, infrastructure. However, the mechanistic underpinnings of ABMs, which couple together different processes, may mean that partial data obtained intermittently constrain the model more strongly when using multiple observational patterns, than when data in different dimensions is considered independently. Where sensitivity analysis shows interactions between parameters, this may help to pick out the appropriate datasets, eliminate certain classes of models or reduce the parameter ranges. Here lies the real power of *Big Data*, in its use as a model constraint, provided that the model couplings across different scales and dimensions are included in sufficient detail. Such models, in contrast to being data-driven, are theory-driven but data-constrained. However, data to approach these challenges are only now becoming available for implementation.

3.3 Results interpretation and uncertainty assessment

Model application should match the target audience as simulation results can be assessed as correct or incorrect simply because, e.g. the visualizations do not represent the results in a manner that is understandable or useful to the user. Besides the technical issues addressed here in trying to interpreting simulation results and assess inherent uncertainties, there are open challenges relating to identifying the needs of different decision-makers and communication of the results in an appropriate manner. Matching these needs to the interpretation of the model results in an automated fashion could significantly increase the efficacy in the use of the model, e.g. as a distributed cognition system [105, 108].

There are different challenges specific to synthesizing ABM output across-scale as well as different sources of uncertainty. It is not only that ABMs may be using *Big Data* as input or calibration and validation data, ABMs are also producers of large, high-dimensional data sets. Thus, while increasing computing power enables us to simulate systems of interest in ever greater detail, synthesis of model results is far from trivial [105]. This may further require distributed, parallel computing systems, or server-/cloud-based network architecture to meet the high computational demands needed to complete simulations in a reasonable time as is quite common in climate change and hydrological modelling applications to date. On the other hand, it is not only computational power that might restrict model size;usability and user understanding which might 'self-restrict' the size of the model as well [67]. In addition, open questions remain as regards the representation and thus identification of spatial structures across scales in models [110], as well as the uncertainty in results due to the model structure. For example, inconsistencies in assumptions between different models being coupled might lead to erroneous results [90], or emergent behaviour might simply be an artefact of the chosen modularization of the model [111]. Upscaling and downscaling of input data to match represented scales in the model or of intermediate results to bridge scales is another source of uncertainty inherent to ABM across-scale [e.g. 112].

One approach to synthesize an ABM across-scale can be to estimate a reduced-form description of the effective dynamics on a different system level, using for example mean-field approximations that study the expected trajectory of the system [e.g. 113-115]. Pagel et al. [116] used this approach to reduce a spatially-explicit ABM in the context of grassland conservation management, to a spatially non-explicit deterministic matrix population model. In this way, reduced-form models link microscopic behavior with properties and dynamics on other scales. Other approaches to reduced-form descriptions of agent-based simulations include the equation-free framework, which enables the analysis of macroscopic patterns without requiring an associated equation [117, 118] and approaches that cluster state space in such a way that the dynamics on the partition are approximately *Markovian* [119-121]. These reduced-form models not only support the analysis of agent-based models, they lead also to more efficient simulations over longer time horizons or for larger populations and can be a basis for bridging across scales. However, care must be taken to ensure that the appropriate dynamics are adequately captured so that the illusion of simplicity does not lead to misinterpretation. For example, since model outcomes of spatially-explicit ABMs are scale-dependent, and the scale dependency may change over time, models may need to be run at various spatial scales, and possibly nested with coarse scale or reduced form models providing boundary conditions for more fine-scale or detailed simulations in areas of interest. One pattern matching approach that builds on fitting multiple resolutions is for example *spatial windowing* [122, 123].

A number of authors propose using ABMs as virtual laboratories to simplify the view of SESs to reveal “first principles of human environment interaction” [124], or even suggest providing “agent based models as a service” [23], or through the use of simplified web interfaces [125]. What we still lack, however, are the long time series and multiple examples of ABM run against real-world case studies that are required to reveal which types of model work well, and which do not. *Big Data* cannot fix this by itself – we need to keep developing models in concert with data gathering to build up the necessary experience over time. Even so, the complexity and boundary/initial condition sensitivity of the models, together with our limited understanding of human decision making, may fundamentally limit the degree of detail that our models can reproduce: the types and characteristics of output may be captured, in a statistical sense, but timing and size of specific individual events are likely to remain beyond the reach of forecasting.

4: Conceptual and methodological directions

Cross-scale issues have been recognised as challenging for adaptation and climate change [126, 127], governance and SESs such as the collapse of cooperation across scales when two groups/communities are connected through resource flows [32, 65], political systems and the withdrawal of the state [128], political economy and resource management [129], and human aspects of global change more generally [31]. The idea that social attitudes may be important for climate change policy modelling goes back at least to Janssen and de Vries [130], although current integrated assessment models for climate remain fixed in traditional frameworks [131]. However, an exclusive focus on climate misses important factors, such as the environmentally damaging consequences of cascading collapses of fisheries across the world or global trade imbalance [e.g. 132]. Consideration of SESs may miss further important aspects of technical and infrastructural aspects that are so far not well represented in the underlying theories [e.g. 66]. Many modellers are well aware that there are cross-scale interactions between systems which can considered independent but in the long term impact each other(see also [12, 13, 15, 16, 19]). Hence the overall aim will be to balance model complexity and the simulated interactions between systems cross-scale to derive outputs that are meaningful and help to derive implications for decision making and policy design[133, 134]. This leads us to make the following suggestions:

1. Acknowledge scale to be a dynamic issue

What process scale is relevant for a particular SES's outcomes can change over time and depend on inter-system couplings. This may mean having to run models at multiple scales in order to capture the possibilities of tipping points, phase changes or cascading failure, for example. In particular, spatially isolated case studies that need to run for many years should allow for changes at the boundary, possibly driven by a coarser scale model or equivalent length time series data.While available computing power enables us to simulate such cross-scale interactions in ever greater detail, this can only be made possible using modular modelling structures such as are available in NetLogo, but more importantly will require larger-scale distributed computing systems rather than a single desktop or laptop. Where model run-time is long but acceptable, then cloud-based approaches using platforms such as Microsoft Azure© or Amazon AWS© might be sufficient to allow for the multiple model runs needed for parameter space exploration or what-if scenario generation. Where models need to be accelerated even in single runs (models so large that run-times might otherwise be months or even years) more traditional high performance computing architectures can be exploited with frameworks such as RepastHPC, which provides the ability to scale to very large numbers (billions) of agents in both gridded and networked configurations[135]. Some of the associated technical difficulties in dealing with this kind of large model in languages like Java are covered in [96].

2. Traditional links between scales may lose validity or be transformed by the superimposition of newly emerging cross-scale links

We have been used to rather stable characteristic spatio-temporal relationships in biology/ecology between space, time and organizational levels: e.g. cell dynamics to be studied over seconds/minutes and at the spatial scale of microns (small size, lower organizational level, short time steps), moving to higher scales with increasing dimensions, such as populations, studied on an annual basis over landscapes of several squared kilometres in size, and countries at scales of decades. This may no longer be true as there are also emerging cross-scale links that also need to be taken into consideration, e.g. in the case of the global finance systems with relevant dynamics within fractions of seconds. Price fluctuations can then trigger outbreaks of violence and collapse of political systems far from their origin. On the other hand, resource exhaustion and associated ecosystem degradation may play out over decades, but couple together remote locations across the globe through the effects of trade networks and link to fast dynamics in political and financial systems. Again, isolated case study locations will struggle to deal with this kind of phenomenon.

3. Adequate representation of governance structure

Governance, i.e. actors and institutions involved in managing SESs, has been rarely and overall not adequately represented in agent-based models to date: here traditional single-agent economics focusing on *homo economicus* is not enough. The multi-scalar, multi-actor nature of governance systems requires careful simulation, including the range of human individual and collective behaviour that such systems display. To model the influence of relevant actors on the selected dynamics across scales, we need to collect data to inform their behaviours. As increasingly recognised by literature on cross-scale dynamics, research should directly involve policy-makers and practitioners to identify questions and develop tools that will prove useful to address environmental governance problems [136]. However, stakeholder views of relevant scales may be limited by their previous experience: this may mean moving them out of their comfort zone, and not relying on the stakeholders or other experts to be the sole determinants of the model ontology. For this reason, we advocate for a significant use of participatory methods in the design of experiments aimed at collecting behavioural data for key stakeholders for example using scenario workshops [137, 138] or role-playing games [139, 140]. These workshops can be designed in multiple ways, but usually rely on the provision of scenarios regarding plausible future situations, to which participants need to respond [141]. This method has proven successful in raising awareness in participants towards specific subjects (e.g. unintended consequences of behaviours implemented, see for instance [142]). Robust statistical methods for the identification of representative stakeholders to be involved in the participatory process are crucial. On the other hand, there is also a need to adopt a reflexive position to take into account the complexity of the social contexts and to strategically deal with existing power asymmetries among stakeholders [143].

Sketching the phases of a research project can help to operationalise the ideas discussed above as part of such an ABM development cycle.While using the example of international food trade, the first step could involve mapping relevant actors across different scales and levels, e.g. (i) relevant ministries such as foreign affairs and trade for the decisions made in regards to international agreements and agriculture to capturechanging policies that affect agricultural practises and crops grown; (ii) multi-national firms as they are especially relevant as price makers in the food sector, due to their big role in agricultural technology development, and their influence on policies through lobbying; (iii) farming communities and associations as they represent the primary sector, receive and implement policies and the same timelobby governments. This would be followed by scoping interviews with representatives from the key actors to identify what dynamics they influence, and how they interact with other stakeholders. Further interviews could be undertaken with actors that have been identified as relevant by the first round of interviews and were not involved. Part of the interviews could involve questions aimed at mapping both actors and relationships between them. The second stage of the project could involve scenario-based workshops with key members of relevant stakeholder groups, where they will be presented with a future scenario (e.g. future drought in Ukraine will result in 8% cereal production loss), and their responses to different checkpoints captured in the scenario (e.g. drought results in a 100% increase in the international price. What is the reaction of the actors?). Once this information has been collected and collated, the development of a meta-model for the behaviour of these actors could start by generating a general framework of responses for each actor based on their reactions to prompts or be informed by relevant theories from cognitive and behavioural sciences. Follow-up interviews could be organised with key stakeholders to fill the gaps or clarify specific reactions and therefore finalise the behavioural meta-model for the different actors.

4. Infrastructure and technology as part of SESs

Put more emphasis on technical and infrastructure issues in SESs descriptions and frameworks. There are almost no *pristine* ecosystems, and the built environment has a major impact on ecosystems, but is multi-scalar in nature. These infrastructure systems are themselves complex and often composed of multiple overlapping networks. As data from *smart cities* and building infrastructure management systems begins to come online, the data on the built environment will only become richer and more detailed. The effects of these human developments on ecosystems is non-trivial, widespread and changing over time. We need to include it on our SESs models.

5. Big Data vs. Big Understanding

Machine learning has promise for analysis of interpretation of complex model output, especially to see where and when scale separation is important, and for suggesting ways to reduce complexity when confronted with modelling scaling-up or scaling-down. *Big Data* has promise for calibration and validation, especially in the light of pattern-oriented modelling or data assimilation but is not a substitute for theoretical underpinnings, particularly as *Big Data* may be heavily biased (consider e.g. social media echo chambers), partial (satellite data obscured by clouds), temporally- or spatially-limited (e.g. public transport data from a single city) or highly aggregated (10-yearly census data records). We therefore also need *Big Understanding* to actually make sense of the data, select the relevant parts, and to guide further data gathering effort by creating data-constrained but process-based models. In this way

we make tools to help people who are overwhelmed by the amount of information and do not have the means to discern between authoritative and inaccurate information.
The use of machine learning to understand complex model output will require significant computational resources (i.e. cloud-based or multi-core/multi-node systems)and the development of models that can run fast enough in an individual or parallel-sense. Even so, use of *black box* machine learning, such as the highly successful deep learning tools now available, may not only make insight difficult, but be misleading where the tools report high accuracy despite being incorrect. More transparent ways to archive and interpret machine learning outputs are needed[144].

6. Using participatory, transdisciplinary procedures to keep model output users 'close-by'
Models play different roles in scientific investigations, the management of SESs, policy appraisals (*ex-ante* analysis) and evaluation (*ex-post* analysis) [4]. Keeping the user of modelling results *close-by* is essential to avoid the tendency of modellers of ABM to focus too much on the question of how to represent SESs and too little on how to actually learn from these models. Thus, we recommend iterative model development where early simplified model versions are thoroughly analysed, with all relevant model outputs and testing methods implemented. Participatory procedures [e.g. 145, 146] and transdisciplinary frameworks [e.g. 147] can play a prominent role in this. Co-design and co-production of research are becoming more and more acknowledged as important components of ABM [57], although, the participatory, transdisciplinary approach is not necessarily straightforward. Deciding who should be involved at which part of a modelling cycle is complex and different actors and stakeholders can have diverse interests. For example, interrogation of models and model results can be done quantitatively (i.e. through multiple simulations, sensitivity analysis, or 'what-if' tests), but may also be done in qualitative and participatory fashion, with stakeholders involved in the actual design as opposed to just being shown the results, see for example Le Page et al. [148]. The choice should be driven by the purpose of the modelling process and the needs of stakeholders. In both *ex-ante* and *ex-post* evaluation, using ABMs across scales can be a powerful tool to use as a route for engaging and informing stakeholders, including the public, about policies and their implications [149]. This may be by including stakeholders in the process, decisions, and validation of model design; or it may be later in the process, in using the results of a model to open up discussions with stakeholders, and/or even using the model *live* to explore connections between assumptions, scenarios, and outcomes [150].

5. Concluding remarks
The issues we have discussed here emphasize the need for ABM of SESs to include the feedbacks that are implied by the presence of both multiple time and spatial scales. The core proposition of this paper is that in a world that is increasinglyrecognized as being connected and multi-scale, solutions must be as

well. This might lead to complex and intricate models, but perhaps the complexity of the real world requires us to embrace this in our modelling efforts. While large scale modelling has received much criticism in the past [151], most of these issues could be addressed by increasing computing power [152], and can be further overcome by ensuring transparency and reproducibility of model code and clarity of model purpose.

Teleconnections in our globalized human-environment system now mean that in practice anything less than global scale modelling is not likely to be able to address any of the pressing policy problems of our time. These go beyond climate change to encompass pandemics, financial instability, resource exhaustion, ecosystem collapse and species extinctions, persistent global poverty, inequality and overconsumption, food security, civil violence, state failures and warfare. The implication is that a global effort is needed to make progress in assessment of and encourage development of ABM approaches that enables the simulation of SESs across scales in all facets. Such an effort needs to involve multiple research groups across the globe, taking a multiplicity of approaches into account, preferably sharing and jointly developing their model code. It should not only focus on producing models with substantial improvements in their capacity to simulate the socio-economic components of SESs, but more importantly should be inclusive, transparent, well tested and, as far as possible, using open sourcemodel code and data policies to make it available to all.

References

1. Berkes F, Folke C (1998) Linking social and ecological systems: management practices and social mechanisms for building resilience, Cambridge University Press, Cambridge

2. Redman CL, Grove JM, Kuby LH (2004) Integrating Social Sciences into the Long-Term Ecological Research (LTER) Network: Social Dimensions of Ecological Change and Ecological Dimensions of Social Change. Ecosystems 7(2):161-171

3. Folke C, Hahn T, Olsson P, Norberg J (2005) Adaptive Governance of Social-Ecological Systems. Annu Rev Environ Resour 30:441-473

4. Verburg PH, Dearing JA, Dyke JG, van der Leeuw S, Seitzinger S, Steffen W, Syvitski J (2016) Methods and approaches to modelling in the Anthropocene. Global Environ Chang 39:328-340

5. Anderies JM, Janssen MA, Ostrom E (2004) A Framework to Analyze the Robustness of Social-ecological Systems from an Institutional Perspective. Ecology and Society 9(1):18

6. McGinnis MD, Ostrom E (2014) Social-ecological systems framework: initial changes and continuing challenges. Ecology and Society 19(2):30

7. Leslie HM, Basurto X, Nenadovic M, Sievanen L, Cavanaugh KC, Cota-Nieto JJ, Erisman BE, Finkbeiner E, Hinojosa-Arango G, Moreno-Báez M, Nagavarapu S, Reddy SM, Sánchez-Rodríguez A, Siegel K, Ulibarria-Valenzuela JJ, Weaver AH, Aburto-Oropeza O (2015) Operationalizing the social-ecological systems framework to assess sustainability. PNAS 112(19):5979-5984

8. Polhill JG, Filatova T, Schlüter M, Voinov A (2016) Modelling systemic change in coupled socio-environmental systems. Environmental Modelling & Software 75:318-332

9. Schlüter M, McAllister RRJ, Arlinghaus R, Bunnefeld N, Eisenack K, Hölker F, Milner-Gulland EJ, Müller B, Nicholson E, Quaas M, Stöven M (2012) New horizons for managing the environment: a review of coupled social-ecological systems modeling. Nat Resour Model 25(1):219-272

10. Virapongse A, Brooks S, Metcalf EC, Zedalis M, Gosz J, Kliskey A, Alessa L (2016) A socio-ecological systems approach for environmental management. J Environ Manage 178:83-91

11. An L (2012) Modeling human decisions in coupled human and natural systems: Review of agent-based models. Ecol Model 229:25-36

12. Filatova T, Verburg PH, Parker DC, Stannard CA (2013) Spatial agent-based models for socio-ecological systems: Challenges and prospects. Environmental Modelling & Software 45:1-7

13. Matthews RB, Gilbert NG, Roach A, Polhill JG, Gotts NM (2007) Agent-based land-use models: a review of applications. Landscape Ecology 22(10):1147-1459

14. Parker DC, Manson SM, Janssen MA, Hoffmann MJ, Deadman P (2003) Multi-agent systems for the simulation of land-use and land-cover change: A review. Ann Assoc Am Geogr 93(2): 314-337

15. Balbi S, Giupponi C (2009) Reviewing agent-based modelling of socio-ecosystems: a methodology for the analysis of climate change adaptation and sustainability. Working Paper Department of Economics, Ca' Foscari University of Venice, No. 15/WP/2009, ISSN: 1827/336X

16. Groeneveld J, Müller B, Buchmann CM, Dressler G, Guo C, Hase N, Hoffmann F, John F, Klasseert C, Lauf T, Liebelt V, Nolzen H, Pannicke N, Schulze J, Weise

H, Schwarz N (2017) Theoretical foundations of human decision-making in agent-based land use models - A review. Environmental Modelling & Software 87:39-48

17. Heckbert S, Baynes T, Reeson A (2010) Agent-based modelling in ecological economics. Ann N Y Acad Sci 1185:39-53

18. Rounsevell MDA, Robinson DT, Murray-Rust, D (2012a) From actors to agents in socio-ecological systems models. Philos Trans R Soc B Biol Sci 367:259-269

19. Schulze J, Müller B, Groeneveld J, Grimm V (2017). Agent-Based Modelling of Social-Ecological Systems: Achievements, Challenges, and a Way Forward. Journal of Artificial Societies and Social Simulation 20(2):8

20. Gog JL, Pellis L, Wood JLN, McLean AR, Arinaminpathy N, Lloyd-Smith JO (2015) Seven challenges in modeling pathogen dynamics within-host and across scales. Epidemics 10:45-48

21. Delli Gatti D, Gallegati M, Greenwald B, Russo A, Stiglitz JE (2010) The financial accelerator in an evolving credit network. J Econ Dyn Control 34: 1627-1650

22. Stiglitz JE, Gallegati M (2011) Heterogeneous Interacting Agent Models for Understanding Monetary Economies. East Econ J 37:6-12

23. Waldrop MM (2018) Free Agents. Science 360:144-147

24. Kiyono K, Struzik ZR, Yamamoto Y (2006) Criticality and Phase Transitions in Stock-Price Fluctuations. Phys Rev Lett 96:068701

25. Arneth A, Brown C, Rounsevell MDA (2014) Global models of human decision-making for land-based mitigation and adaptation assessment. Nat Clim Change 4:550-558

26. Rounsevell MDA, Pedroli B, Erb K-H, Gramberger M, Busck AG, Haberl H, Kristensen S, Kuemmerle T, Lavorel S, Lindner M, Lotze-Campen H, Metzger MJ, Murray-Rust D, Popp A, Perez-Souba M, Reenberg A, Vadineanu A, Verburg PH, Wolfslehner B (2012b) Challenges for land system science. Land Use Policy 29(4):899-910

27. Haining R (2003) Spatial Data Analysis: Theory and Practice. Cambridge University Press, Cambridge

28. Lloyd CD (2014) Exploring spatial scale in Geography. Wiley, Chichester

29. Marston SA, Jones JP III, Woodward K (2005) Human Geography without Scale. Trans Inst Br Geogr 30:416-432

30. Montello DR (2001) Scale in Geography. In: Smelser NJ, Baltes B (eds) International Encyclopedia of the Social and Behavioral Sciences. Elsevier, pp 13501-13504

31. Gibson CC, Ostrom E, Ahn TK (2000) The concept of scale and the human dimensions of global change: a survey. Ecol Econ 32(2):217-239

32. Cash DW, Adger NW, Berkes F, Garden P, Lebel L, Olsson P, Pritchard L, Young O (2006) Scale and cross-scale dynamics: governance and information in a multilevel world. Ecology and Society 11(2):8

33. Lebel L, Garden P, Imamura M (2005) The politics of scale, position and place in the management of water resources in the Mekong region. Ecology and Society 10(2): 18

34. Young O (2006) Vertical interplay among scale-dependent environmental and resource regimes. Ecology and Society 11(1):27

35. Gotts NM, Polhill JG (2006) Simulating Socio-Techno-Ecosystems. Proceedings of the First World Congress on Social Simulation (WCSS 2006), Kyoto University, Kyoto, Japan, 21-25 August 2006, pp 119-126

36. Hofstede GJ (2018) Mental Activity and Culture: The Elusive Real World. In: Faucher C (ed) Advances in Culturally-Aware Intelligent Systems and in Cross-Cultural Psychological Studies. Cham, Springer International Publishing, pp 143-164

37. Foley JA, DeFries R, Asner GP, Barford C, Bonan G, Carpenter SR, Chapin FS, Coe MT, Daily GC, Gibbs HK, Helkowski JH, Holloway T, Howard EA, Kucharik CJ, Monfreda C, Patz JA, Prentice IC, Ramankutty N, Snyder PK (2005) Global consequences of land use. Science 309 (5734):570-574

38. Schlüter M, Baeza A, Dressler G, Frank K, Groeneveld J, Jager W, Jansse MA, McAllister RRJ, Müller B, Orach K, Schwarz N, Wijermans N (2017) A framework for mapping and comparing behavioural theories in models of social-ecological systems. Ecol Econ 131:21-35

39. Hofstede GJ (2017) GRASP agents: social first, intelligent later. Ai & Society: 1-9

40. Carpenter SR, Mooney HA, Agard J, Capistrano D, DeFries RS, Díaz S, Dietz T, Duraiappah AK, Oteng-Yeboah A, Pereira HM, Perrings C, Reid WV, Sarukhan J,

Scholes RJ, Whyte A (2009) Science for managing ecosystem services: Beyond the Millennium Ecosystem Assessment. Proceedings of the National Academy of Sciences 106(5):1305-1312

41. Müller D, Munroe DK (2014) Current and Future Challenges in Land-Use Science. Journal of Land Use Science 9(2):133-42

42. Colander D (2006) Post Walrasian Macroeconomics: Beyond the Dynamic Stochastic General Equilibrium Model. Cambridge University Press, New York

43. Sonnenschein H (1972) Market Excess Demand Functions. Econometrica 40(3):549-563

44. Debreu G (1974) Excess Demand Functions. Journal of Mathematical Economics 1(1):15-23

45. Kirman AP (1992) Whom or What Does the Representative Individual Represent? Journal of Economic Perspectives 6(2):117-136

46. Balke T, Gilbert N (2014) How Do Agents Make Decisions? A Survey. Journal of Artificial Societies and Social Simulation. 17(4):13

47. Epstein JM, Axtell RL (1996) Growing Artificial Societies: Social Science from the Bottom Up, The MIT Press

48. Tesfatsion L, Judd KL (2006) Handbook of Computational Economics. Vol. 2, Agent-Based Computational Economics. Elsevier, Amsterdam

49. LeBaron B, Tesfatsion L (2008) Modeling Macroeconomies as Open-Ended Dynamic Systems of Interacting Agents. American Economic Review 98(2):246-250

50. Raberto M, Teglio A, Cincotti S (2012) Debt Deleveraging and Business Cycles. An Agent-Based Perspective. Economics: The Open-Access, Open-Assessment E-Journal http://dx.doi.org/10.5018/economics-ejournal.ja.2012-27

51. Delli Gatti D, Di Guilmi C, Gaffeo E, Giulioni G, Gallegati M, Palestrini A (2005) A new approach to business fluctuations: heterogeneous interacting agents, scaling laws and financial fragility. Journal of Economic Behavior & Organization 56(4):489-512

52. Farmer JD, Hepburn C, Mealy P, Teytelboym A (2015) A Third Wave in the Economics of Climate Change. Environ Resource Econ 62(2):329-357

53. Lamperti F, Dosi G, Napoletano M, Roventini A, Sapio A (2017a) Faraway, So Close: Coupled Climate and Economic Dynamics in an Agent-Based Integrated Assessment Model LEM Working Paper Series. Available at SSRN:https://ssrn.com/abstract=2944328 orhttp://dx.doi.org/10.2139/ssrn.2944328

54. Lustick IS, Alcorn B, Garces M, Ruvinsky A (2012) From theory to simulation: the dynamic political hierarchy in country virtualisation models. Journal of Experimental & Theoretical Artificial Intelligence 24(3):279-299

55. Natalini D, Bravo G, Jones AW (2017) Global food security and food riots–an agent-based modelling approach. Food Security:1-21. Doi:10.1007/s12571-017-0693-z.

56. Ferrier S, Ninan KN, Leadly P, Alkemade R, Acosta LA, Akçakaya HR, Brotons L, Cheung WWL, Christensen V, Harhash KA, Kabubo-Mariara J, Lundquist C, Obersteiner M., Pereira HM, Peterson G, Pichs-Madruga R, Ravindranath N, Rondinini C, Wintle BA (2016) IPBES (2016): The methodological assessment report on scenarios and models of biodiversity and ecosystem services. Secretariat of the Intergovernmental. Science-Policy Platform on Biodiversity and Ecosystem Services, Bonn, Germany

57. Gilbert N, Ahrweiler P, Barbrook-Johnson P, Narasimhan KP, Wilkinson H (2018) Computational Modelling of Public Policy: Reflections on Practice. Journal of Artificial Societies and Social Simulation 21(1):14

58. Janssen MA, Walker BH, Langridge J, Abel N (2000) An adaptive agent model for analysing co-evolution of management and policies in a complex rangeland system. Ecological Modelling 131(2-3):249-268

59. Gross JE, McAllister RJJ, Abel N, Stafford Smith DM, Maru Y (2006) Australian rangelands as complex adaptive systems: A conceptual model and preliminary results. Environmental Modelling and Software 21(9):1264-1272

60. Cioffi-Revilla C, Rouleau M (2010) MASON RebeLand: An agent-based model of Politics, Environment,and Insurgency. International Studies Review 12(1):31-52

61. Gerst MD, Wang P, Roventini A, Fagiolo G, Dosi G, Howarth RB, Borsuk ME (2013) Agent-based modelling of climate policy: An introduction to the ENGAGE multi-level model framework. Environmental Modelling and Software 44:62-75

62. Greeven S, Kraan O, Chappin EJL, Kwakkel JH (2016) The Emergence of Climate Change Mitigation Action by Society: An Agent-based Scenario Discovery Study. Journal of Artificial Societies and Social Simulation 19(3):9

63. Dubbelboer J, Nikolic I, Jenkins K, Hall J (2017) An Agent-based Model of Flood Risk and Insurance. Journal of Artificial Societies and Social Simulation 20(1):6

64. Muis J (2010) Simulating Political Stability and Change in the Netherlands (1998-2010): an Agent-Based Model of Party Competition with Media Effects Empirically Tested. Journal of Artificial Societies and Social Simulation 13(2):4

65. Brondizio ES, Ostrom E, Young OR (2009) Connectivity and the Governance of Multilevel Social-Ecological Systems. Annu Rev Env Resour 34:253-278

66. Ostrom E (2009) A general framework for analyzing sustainability of social-ecological systems. Science 325(5939):419-422

67. Armitage DR, Plummer R, Berkes F, Arthur RI, Charles AT, Davidson-Hunt IJ, Diduck AP, Doubleday NC, Johnson DS, Marschke M, McConney P, Pinkerton EW, Wollenberg EK (2009) Adaptive co-management for social-ecological complexity. Frontiers in Ecology and the Environment 7(2):95-102

68. Grimm V, Ayllón D, Railsback SF (2017) Next-generation Individual-Based Models Integrate Biodiversity and Ecosystems: Yes We Can and Yes We Must. Ecosystems 20(2):229-236

69. Luus KA, Robinson DT, Deadman PJ (2013) Representing ecological processes in agent-based models of land use and cover change. J Land Use Sci 8(2):175–198

70. Huigen MGA (2004) First principles of the MameLuke multi-actor modelling framework for land use change, illustrated with a Philippine case study. J Environ Manage 72(1-2):5-21

71. Bakker MM, Govers G, Kosmas C, Vanacker V, van Oost K, Rounsevell MDA (2005) Soil Erosion as a Driver of Land-Use Change. Agriculture, Ecosystems and Environment 105(3): 467-481

72. Eichner T, Pethig R (2005) Ecosystem and Economy: An Integrated Dynamic General Equilibrium Approach. Journal of Economics 85(3):213-249

73. Lindkvist E, Basurto X, Schlüter M (2017) Micro-level explanations for emergent patterns of self-governance arrangements in small-scale fisheries—A modeling approach. PLoS ONE 12(4): e0175532. https://doi.org/10.1371/journal.pone.0175532

74. Martin R, Schlüter M (2015) Combining system dynamics and agent-based modeling to analyze social-ecological interactions – an example from modeling restoration of a shallow lake. Frontiers in Environmental Science 3:66

75. Manson SM (2005) Agent-based modeling and genetic programming for modeling land change in the Southern Yucatán Peninsular Region of Mexico. Agric Ecosyst Environ 111(1-4):47–62

76. Gaube V, Kaiser C, Wildenberg M, Adensam H, Fleissner P, Kobler J, Lutz J, Schaumberger A, Schaumberger J, Smetschka B, Wolf A, Richter A, Haberl H (2009) Combining agent-based and stock-flow modelling approaches in a participative analysis of the integrated land system in Reichraming, Austria. Landsc Ecol 24(9):1149–1165

77. Bagstad KJ, Johnson GW, Voigt B, Villa F (2013) Spatial dynamics of ecosystem service flows: A comprehensive approach to quantifying actual services. Ecosyst Serv 4:117-125

78. Bithell M, Brasington J (2009) Coupling Agent-based models of subsistence farming with individual-based forest models and dynamic models of water distribution. Environmental Modelling and Software 24(2):173-190

79. Guillem EE, Murray-Rust D, Robinson DT, Barnes A, Rounsevell MDA (2015) Modelling farmer decision-making to anticipate tradeoffs between provisioning ecosystem services and biodiversity. Agric Syst 137:12–23

80. Bonan GB, Doney SC (2018) Climate, ecosystems, and planetary futures: The challenge to predict life in Earth system models. Science 359(6375), eaam8328, DOI: 10.1126/science.aam8328

81. Purves D, Scharlemann JPW, Harfoot M, Newbold T, Tittensor DP, Hutton J, Emmott S (2013) Ecosystems: Time to model all life on earth. Nature 493:295-297

82. Evans MR, Bithell M, Cornell SJ, Dall SRX, Díaz S, Emmott S, Ernande B, Grimm V, Hodgson DJ, Lewis SL, Mace GM, Morecroft M, Moustakas A, Murphy E, Newbold T, Norris KJ, Petchey O, Smith M, Travis JMJ, Benton TG (2013) Predictive systems ecology. Proc Roy Soc B 280:20131452, http://dx.doi.org/10.1098/rspb.2013.1452

83. Harfoot MBJ, Newbold T, Tittensor DP, Emmott S, Hutton J, Lyutsarev V, Smith MJ, Scharlemann JPW, Purves DW (2014) Emergent Global Patterns of Ecosystem Structure and Function from a Mechanistic General Ecosystem Model. PLoS Biol 12(4): e1001841. https://doi.org/10.1371/journal.pbio.1001841

84. Titeux N, Henle K, Mihoub J-B, Regos A, Geijzendorffer IR, Cramer W, Verburg PH, Brotons L (2016) Biodiversity scenarios neglect future land-use changes. Global Change Biology 22:2505-2515

85. van Dam KH, Nikolic I, Lukszo Z (2013) Agent-based modelling of Socio-Technical Systems. Agent-Based Social Systems 9, Springer

86. Barber CP, Cochrane MA, Souza CN Jr., Laurance WF (2014) Roads, deforestation and the mitigating effect of protected areas in the Amazon. Biological Conservation 177:203-209

87. Millington JDA, Xiong H, Peterson S, Woods J (2017) Integrating Modelling approaches for Understanding Telecoupling: Global Food Trade and Local Land Use. Land 6(3):56

88. Parker DC, Hessl A, Davis SC (2008) Complexity, land-use modeling, and the human dimension: Fundamental challenges for mapping unknown outcome spaces. Geoforum 39(2): 789-804

89. Pacilly FCA, Hofstede GJ, van Bueren ETL, Kessel GJT, Groot JCJ (2018) Simulating crop-disease interactions in agricultural landscapes to analyse the effectiveness of host resistance in disease control: The case of potato late blight; Ecological Modelling 378:1-12

90. FCA Pacilly (2018) Social-ecological modelling of potato late blight. Managing crop resistance in disease. PhD Thesis, Wageningen University, 175p

91. Voinov A, Shugart HH (2013) ‘Integronsters’, integral and integrated modeling. Environmental Modelling and Software 39:149-158

92. Wolf S, Hinkel J, Hallier M, Bisaro A, Lincke D, Ionescu C, Klein RJT (2013) Clarifying vulnerability definitions and assessments using formalisation. International Journal of Climate Change Strategies and Management 5:54-70

93. Axelrod R (2006) Agent-based modeling as a bridge between disciplines, in: Tesfatsion L, Judd KL (eds) Handbook of Computational Economics, Elsevier, Vol 2, pp 1565-1584

94. Polhill JG, Gotts NM (2009) Ontologies for transparent integrated human-natural system modelling. Landscape Ecology 24:1255-1267

95. Janssen S, Andersen E, Athanasiadis IN, van Ittersum M (2008) An European database for integrated assessment and modeling of agricultural systems. In: Sànchez-Marrè M, Béjar J, Comas J, Rizzoli A, Guariso G (eds) Proceedings of the 4th Biennial Meeting of the International Environmental Modeling and Software Society (iEMSs). Barcelona, Spain, pp 719-726

96. Bosch J (2014) Continuous software engineering. Springer International Publishing

97. Herbsleb JD (2007) Global Software Engineering: The Future of Socio-technical co-ordination. Future of Software Engineering, 188-198, IEEE Computer Society

98. Parker J, Epstein JM (2011) A distributed Platform for Global-Scale Agent-Based Models of Disease Transmission. ACM Transactions on Modeling and Computer Simulation 22(1):1-25

99. Parry HR, Bithell M (2012) Large scale agent-based modelling: A review and guidelines for model scaling. In: Heppenstall AJ, Crooks AT, See LM, Batty M (eds) Agent-based models of Geographical Systems. Springer, Dordrecht, pp 271-308

100. Smajgl A, Brown DG, Valbuena D, Huigen MGA (2011) Empirical characterisation of agent behaviours in socio-ecological systems. Environmental Modelling & Software 26(7):837-844

101. Müller-Hansen F, Schlüter M, Mäs M, Donges JF, Kolb JJ, Thonicke K, Heitzig J (2017) Towards representing human behavior and decision making in Earth System models – an overview of techniques and approaches. Earth System Dynamics 8:977-1007

102. Kitchin R. (2013) Big data and human geography: Opportunities, challenges and risks. Dialogues in Human Geography 3(3):262-267

103. Yang C, Huang Q, Li Z, Liu K, Hu F (2017) Big Data and cloud computing: innovation opportunities and challenges. International Journal of Digital Earth, 10(1):13-53

104. Ward JA, Evans AJ, Malleson NS (2016) Dynamic calibration of agent-based models using data assimilation. R Soc Open Sci 3(4):150703

105. Lee J-S, Filatova T, Ligmann-Zielinska A, Hassani-Mahmooei B, Stonedahl F, Lorscheid I, Voinov A, Polhill G, Sun Z, Parker DC (2015) The complexities of Agent-Based modeling output analysis. Journal of Artificial Societies and Social Simulation 18(4):4

106. Lamperti F, Roventini A, Sani A (2018) Agent-based model calibration using machine learning surrogates. Journal of Economic Dynamics and Control 90:366-389

107. Kattwinkel M, Reichert P (2017) Bayesian parameter inference for individual-based models using a Particle Markov Chain Monte Carlo Method. Environmental Modelling and Software 87:110-119

108. Grimm V, Revilla E, Berger U, Jeltsch F, Mooij WM, Railsback SF, Thulke HH, Weiner J, Wiegand T, DeAngelis DL (2005) Pattern-oriented modeling of agent-based complex systems: lessons from ecology. Science 310:987-991

109. Barrett C, Eubank S, Marathe A, Marathe M, Swarup S (2015) Synthetic information environments for policy informatics: a distributed cognition perspective. In: Johnston EW (ed) Governance in the Information Era: Theory and Practice of Policy Informatics. Routledge, New York, pp 267–284

110. Schulz K, Seppelt R, Zehe E, Vogel HJ, Attinger S (2006) Importance of spatial structures in advancing hydrological sciences. Water Resources Research 42:W03S03

111. Saari DG (2010) Aggregation and multilevel design for systems: Finding guidelines. Journal of Mechanical Design 132(8):081006.

112. Evans TP, Kelley H (2004) Multi-scale analysis of a household level agent-based model of land cover change. Journal of Environmental Management 72(1-2):57-72

113. Galan JM, Izquierdo LR (2005) Appearances can be deceiving: Lessons learned re-implementing Axelrod's 'Evolutionary approach to norms'. Journal of Artificial Societies and Social Simulation 8(3):2

114. Edwards M, Huet S, Goreaud F, Deffuant G (2003) Comparing an individual-based model of behaviour diffusion with its mean field aggregate approximation. Journal of Artificial Societies and Social Simulation 6(4):9

115. Huet S, Edwards M, Deffuant G (2007) Taking into Account the Variations of Neighbourhood Sizes in the Mean-Field Approximation of the Threshold Model on a Random Network. Journal of Artificial Societies and Social Simulation 10(1):10

116. Pagel J, Fritzsch K, Biedermann R, Schröder B (2008) Annual plants under cyclic disturbance regime: better understanding through model aggregation. Ecological Applications 18:2000-2015

117. Martin R, Thomas SA (2016) Analyzing regime shifts in agent-based models with equation-free analysis. In: Sauvage S, Sánchez-Pérez JM, Rizzoli AE (eds) 8th International Congress on Environmental Modelling and Software. Toulouse, France, pp 494-502

118. Zou Y, Fonoberov VA, Fonoberova M, Mezic I, Kevrekidis IG (2012) Model reduction for agent-based social simulation: Coarse-graining a civil violence model, Physical Rev E Stat Nonlin Soft Matter Phys 85:066106

119. Banisch S (2016) Markov chain aggregation for agent-based models. Springer International Publishing

120. Hallier M, Hartmann C (2016) Constructing Markov state models of reduced complexity from agent-based simulation data. Social Simulation Conference 2016, Rome, Italy

121. Niedbalski JS, Deng K Mehta PG, Meyn S (2008) Model reduction for reduced order estimation in traffic models. Proceedings American Control Conference 2008, Seattle, USA

122. Costanza R (1989) Model goodness of fit: A multiple resolution procedure. Ecological Modeling 47(3-4):199-215

123. Pontius RG Jr., Boersma W, Castella J-C, Clarke K, de Nijs T, Dietzel C, Dua Z, Fotsing E, Goldstein N, Kok K, Koomen E, Lippitt CD, McConnell W, Sood AM, Pijanowski B, Pithadia S, Sweeney S, Trung TN, Veldkamp AT, Verburg PH (2008) Comparing the input, output, and validation maps for several models of land change. Annals of Regional Science 42(1):11–37

124. Magliocca NR, van Vliet J, Brown C, Evans TP, Houet T, Messerli P, Messina JP, Nicholas KA, Ornetsmüller C, Sagebiel J, Schweizer V, Verburg PH, Yu Q (2015) From meta-studies to modeling: Using synthesis knowledge to build broadly applicable process-based land change models. Environmental Modelling & Software 72:10-20

125. Deodhar S, Bisset K, Chen J, Barrett C, Wilson M Marathe M (2015) EpiCaster: An Integrated Web Application For Situation Assessment and Forecasting of Global Epidemics. Proceedings of the 6th ACM Conference on Bioinformatics, Computational Biology and Health Informatics.

126. Adger WN, Arnell NW, Tompkins EL (2005a) Successful adaptation to climate change across scales. Global Environmental Change 15(2):77-86

127. Balbi S, Giupponi C, Perez P, Alberti M (2013) A spatial agent-based model for assessing strategies of adaptation to climate and tourism demand changes in an alpine tourism destination. Environmental Modelling and Software 45:29-51

128. Cohen A, McCarthy J (2014) Reviewing rescaling: Strengthening the case for environmental considerations. Progress in Human Geography 39(1):3-25

129. Adger WN, Brown K, Tompkins EL (2005b) The Political Economy of Cross-Scale Networks in Resource Co-Management. Ecology and Society 10(2):9

130. Janssen M, de Vries B (1998) The battle of perspectives: a multi-agent model with adaptive responses to climate change. Ecological Economics 26(1):43-65

131. Stern N (2016) Current climate models are grossly misleading. Nature 530:407-409

132. Wiedmann T, Lenzen M (2018) Environmental and social footprints of international trade. Nature Geoscience 11:314-321

133. Janssen MA, Alessa LN, Barton M, Bergin S, Lee A (2008) Towards a Community Framework for Agent-Based Modelling. Journal of Artificial Societies and Social Simulation 11(2): 6

134. Rollins ND, Barton CM, Bergin S, Janssen MA, Lee A (2014) A Computational Model Library for publishing model documentation and code. Environmental Modelling and Software 61: 59-64

135. Collier N, North M (2012) Repast HPC: A Platform for Large-Scale Agent-Based Modeling; in: Dubitzky W., Kurowski K, Schott B (Eds.) Large-Scale Computing, 202p

136. Vervoort JM, Rutting L, Kok K, Hermans FLP, Veldkamp T, Bregt AK, van Lammeren R (2012) Exploring dimensions, scales, and cross-scale dynamics from the perspectives of change agents in social–ecological systems. Ecology and Society 17(4):24

137. Smajgl A (2010) Challenging beliefs through multi-level participatory modelling in Indonesia. Environmental Modelling and Software 25(11):1470-1476

138. Mazzega P, Therond O, Debril T, March H, Sibertin-Blanc C, Lardy R, Sant'Ana D (2014) Critical Multi-level Governance Issues of Integrated Modelling: An Example of Low-Water Management in the Adour-Garonne Basin (France). Journal of Hydrology 519:2515-2526

139. Castella J-C (2009) Assessing the role of learning devices and geovisualisation tools for collective action in natural resource management: Experiences from Vietnam. Journal of Environmental Management 90(2):1313-1319

140. d'Aquino P, Bah A (2014) Multi-level participatory design of land use policies in African drylands: A method to embed adaptability skills of drylands societies in a policy framework. Journal of Environmental Management 132:207-219

141. Delmotte S, Barbier J-M, Mouret J-C, Le Page C, Wery J, Chauvelon P, Sandoz A, Lopez-Ridaura S (2016) Participatory integrated assessment of scenarios for organic farming at different scales in Camargue, France. Agricultural Systems 143:147-158

142. Lippe M, Hilger T, Sudchalee S, Wechpibal N, Jintrawet A, Cadisch G (2017) Simulating stakeholder-based land-use change scenarios and their implication on Above-Ground Carbon and environmental management in Northern Thailand. Land 6(4):85

143. Barnaud C, Van Paassen A (2013) Equity, Power Games, and Legitimacy: Dilemmas of Participatory Natural Resource Management. Ecology and Society 18(2):21

144. Janssen MA (2017) The Practice of Archiving Model Code of Agent-Based Models. Journal of Artificial Societies and Social Simulation 20(1): 1-2

145. Lippe M, Thai Minh T, Neef A, Hilger T, Hoffmann V, Lam NT, Cadisch G (2011) Building on qualitative datasets and participatory process to simulate land use change in a mountain watershed of Northwest Vietnam. Environmental Modelling & Software 26(12):1454-1466

146. Le Page C, Perrotton A (2017) KILT: A Modelling Approach Based on Participatory Agent-Based Simulation of Stylized Socio-Ecosystems to Stimulate Social Learning with Local Stakeholders. In: Sukthankar G, Rodriguez-Aguilar JA (eds) Autonomous Agents and Multiagent Systems: AAMAS 2017 Workshops, Visionary Papers. Springer, Cham, pp 31-44

147. Allen CR, Fontaine JJ, Pope KL, Garmestani AS (2011) Adaptive management for a turbulent future. Journal of Environmental Management 92(5):1339-1345

148. Le Page C, Bobo KS, Kamgaing OWT, Ngahane FB, Waltert M (2015) Interactive simulations with a stylized scale model to codesign with villagers an agent-based model of bushmeat hunting in the periphery of Korup National Park (Cameroon). Journal of Artificial Societies and Social Simulation 18(1):8

149. Voinov A, Bousquet F (2010) Modelling with stakeholders. Environmental Modelling & Software, 25(11):1268-1281

150. Johnson PG (2015) Agent-based models as “interested amateurs”. Land 4(2):281-299

151. Lee Jr. DB (1973) Requiem for large-scale models. Journal of the American Institute of planners, 39(3):163-178.

152. Lee DB (1994) Retrospective on large scale urban models. Journal of the American Planning Association 60:35-40