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Modelling systemic change in coupled socio-environmental systems

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ABSTRACT

Abrupt systemic changes in ecological and socio-economic systems are a regular occurrence. While there has been much attention to studying systemic changes primarily in ecology as well as in economics, the attempts to do so for coupled socio-environmental systems are rarer. This paper bridges the gap by reviewing how models can be instrumental in exploring significant, fundamental changes in such systems. The history of modelling systemic change in various disciplines contains a range of definitions and approaches. Even so, most of these efforts share some common challenges within the modelling context. We propose a framework drawing these challenges together, and use it to discuss the articles in this thematic issue on modelling systemic change in coupled social and environmental systems. The differing approaches used highlight that modelling systemic change is an area of endeavour that would benefit from greater synergies between the various disciplines concerned with systemic change.

1. Introduction

The collapse of ecosystems and the global financial crisis have much more in common than one may think at the first glance (Scheffer, 2009). Not only may these abrupt systemic changes be driven by internal and external processes of a similar nature, the system's reactions and early warning signals that indicate such changes may also share the same characteristics (Scheffer et al., 2009). While there has been much attention to studying regime shifts in ecological and economic systems independently, the attempts to do so for coupled socio-environmental systems (SES) are scarcer. (We deliberately use the term socio-environmental systems here, with a view to being as general as possible, though social-ecological systems are very much in view.) Understanding systemic change in coupled systems requires insights not only into the processes at macro and micro levels in both socio-economic and environmental subsystems but also into the role of feedbacks between them. Models can be instrumental here. This special issue aims to elicit and discuss the challenges of modelling systemic changes in coupled SES and point towards ways to address them by presenting recent examples of simulation models of systemic change. We begin our introduction to the issue using three challenges (terminology, structural change and subjectivity) as a basis for introducing systemic change in coupled socio-environmental systems.

1.1. Terminology and definitions

One of the first obstacles in the study of systemic change in SES is terminology.[1] Various disciplines in both the environmental and social sciences have engaged with relevant ideas – regime shift, structural change, non-marginal change, transition theory to name a few – and each claims ownership over their tokens. While ordinary mortals squabble over land and resources, in academia the territories are linguistic. For the purposes of introducing this thematic issue, we use the term *systemic change*, and include in Box 1 a brief glossary of terms. As modellers, we are interested in *systems* (though even this term is claimed), whether they are represented or analysed using equations, probability distributions, algorithms or any other formal approach. *Systemic changes* involve

[1] Indeed, the concept of coupled socio-environmental systems is itself the subject of debate with different terminology in different disciplines. Here we mean systems that include people embedded in dynamic, evolving environments (such as ecosystems) that they depend on but also affect.

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Box 1
Glossary

The definitions here apply to the terms as they are used in this paper. Due to the diversity of disciplines involved in the area, authoritative or normative definitions are infeasible.

Coupled systems – distinct systems that can be modelled in their own right that are linked together.

Domain of attraction – a region of state space a system is inclined to inhabit.

Feedback – a mechanism, process or signal that loops back to influence the SES component emitting the signal or initiating the mechanism or process (Biggs et al., 2015).

Ontology – the entities, attributes, relationships and processes that are explicitly represented in the model's formulae, variables and algorithms.

Regime – the configuration of a social-ecological system, i.e. its self-organizing processes and structures (Biggs et al., 2015).

Regime shift – a substantial reorganization in system structure, functions and feedbacks that often occurs abruptly and persists over time (Crepin et al., 2012).

Social-ecological systems – complex, integrated systems in which humans are embedded in nature (Berkes and Folke, 1998).

Socio-environmental systems – tightly linked social and ecological, biophysical or spatial systems that mutually influence each other (based on SESYNC http://www.sesync.org/).

Systemic change – a fundamental change in the behaviour and/or structure of a system, be it the language used to describe the states it could possibly have, 'significant' changes to the expressions in that language indicating the states it does have, or changes in the descriptions of the processes by which the system moves from one state to the next.

Theoretical model – a conceptual, abstract model, not necessarily fitted to data.

fundamental changes to the way in which a system is structured, covering such things as:

- new classes of entity being formed, or new types of relationship between them;
- the introduction of new processes and changes in feedback loops;
- changes to the set of exogenous variables to which the system is sensitive;
- other changes to the relevance of variables in or affecting the system;
- the reorganisation of networks of interaction, possibly entailing different interaction topologies;
- abrupt (step-wise) changes in functions or parameters describing the system.

All these may be needed to represent exogenous change, or endogenous evolution that comes as a result of the formation of new institutions, rules or norms governing behaviour.

If we conceive systemic change as going from one system α to another, β, then in comparison with models of system α exclusively, models simulating systemic change from α to β entail, to some degree or another, redefinition of system boundaries and pathways through which the social system interacts with its environment. Differences between the two kinds of model may also include appropriate temporal and spatial system resolutions and extent.

Systemic changes may arise through exogenous disturbances to a system or emerge endogenously either through the behaviour of the system itself, or through gradually accumulated responses of the system to relatively small exogenous perturbations (Walker and Meyers, 2004; Biggs et al., 2009; Carpenter et al., 2011). Systemic changes may be coupled with a collapse in existing (formal and informal) institutions, loss of key hubs in interaction networks, irrelevance of prior classification criteria, or entities no longer interrelating in a particular way. To consider a rather extreme example, the French revolution involved the collapse of the monarchy, the execution of much of the aristocracy, the irrelevance of feudal social stratification, and with that, at least in principle, an end to social interactions based on a presumption of inequality. Since such changes may themselves be seen as disturbances, a systemic change can also be understood as the propagation and amplification of a disturbance throughout the system, leading to a long-term change in the way the system is organised. All these issues pose challenges for modelling, not least because, in extreme cases, they may involve a fundamental shift in the vocabulary used to describe the system, which will be reflected in the model's ontology. For example, in equation-based models systemic change implies that not only parameters' or variables' values change but the entire functional forms used to relate them in the model transform, possibly with new variables and new processes being introduced and old ones being deleted.

More formally, a model of a system may be conceived as a triplet consisting of (L) a formal language describing the possible states it can have, (E) expressions in that language describing the specific state it currently has (such as, the existence of a particular entity, values the entity has for its variables, and the other entities it interacts with), and (P) algorithms for computing subsequent state(s) of the system given previous state(s). Systemic change as represented in the model is a change to combinations of L, P, and 'major changes' to E, each of which will be referred to as ΔL, ΔP and ΔE systemic changes respectively. In the case of ΔE, a systemic change occurs when a significant number of the entities in the system are replaced with new entities, but ones of the same types, interacting in the same way as before. In ΔP, the systemic change affects the way the system evolves. In ΔL, it is the whole vocabulary used to describe the system that changes. (See Box 2.) Notably, systemic changes are not necessarily associated with a 'shock' or disturbance – they can occur through the gradual evolution of the system, so are also relevant to those who do not believe in discontinuities in natural systems (the *natura non facit saltus* axiom). Gradual changes in a system's elements and micro-level processes may drive a system over a critical point when irreversible and significant macro-level structural changes occur.

1.2. Change in structure

Another major challenge for modelling systemic changes is that they – by definition – involve fundamental changes in system behaviour and structure that are often unknown beforehand. The promise of predictive modelling, however, is based on the assumption that the trend along which a system was developing in the past can be, with acceptable confidence, extrapolated into the future. We build our models based on what we know about the systems in the past. This is well recognized for statistical or data-

Box 2

Lock-in in FEARLUS as a case study in shocks pushing the model boundary

Early versions of the FEARLUS (Framework for the Evaluation and Assessment of Regional Land Use Scenarios) model were not intended to study shocks, rather to explore the dynamics of heuristic decision-making algorithms in agricultural systems (Polhill et al., 2001; Gotts et al., 2003). However, the study of lock-in in FEARLUS (Gotts and Polhill, 2010) provides an interesting context in which to demonstrate how shocks in socio-environmental systems push the model boundary. FEARLUS is an agricultural land use change agent-based model. It simulates agents representing farm businesses, who must choose each year (the time step of the model) the land uses they will apply to their land parcels. These land uses are then harvested, and the farm business agents accrue wealth from selling the goods, from which is subtracted operating costs. The agricultural yield depends on the exogenous time series of climatic data and spatially varying biophysical characteristics of land parcels as well as endogenous land use decisions of farm business agents. After accruing wealth during each time step, farm business agents with negative wealth sell their land, which may then be bought by their neighbours or by in-migrant agents. The agents are better conceived as farm businesses rather than farmers, as their lifespan is not limited by anything other than the period for which they can maintain non-negative wealth.

In experiments involving what we term 'purely' imitative heuristic decision-making algorithms – those that only choose land uses appearing in the neighbourhood of the agent – all agents can 'lock-in' to a single land use in a finite period of time (Fig. B2.1) (Gotts and Polhill, 2010). This happens when a particular land use remains the most profitable for a sustained period of time that is long enough for all agents to copy it. Once lock-in occurs, assuming purely imitative decision-making algorithms, no agent can choose anything other than the locked-in land use. Bankruptcy of the whole population of agents may then occur quite abruptly when the locked-in land use becomes unprofitable and reserves of wealth are depleted. This mass bankruptcy may be seen as a ΔE systemic change (to use the terminology in the introduction), precipitated by the 'shock' of the locked-in land use no longer being profitable. In-migrant land managers are also 'pure' imitators in these experiments, with the consequence that when the locked-in land use is unprofitable, the in-migrant managers go bankrupt immediately. In such simulation runs, there can be several time steps in which all agents go bankrupt in each time step. In the run shown in Fig. B2.1, the first mass-bankruptcy occurs 100 years or so after lock-in. This time period is a function of the fact that, after lock-in, each agent's wealth is a random walk driven by the way changes in the economy are modelled, with 0 as an absorbing state. (Fig. B2.2).

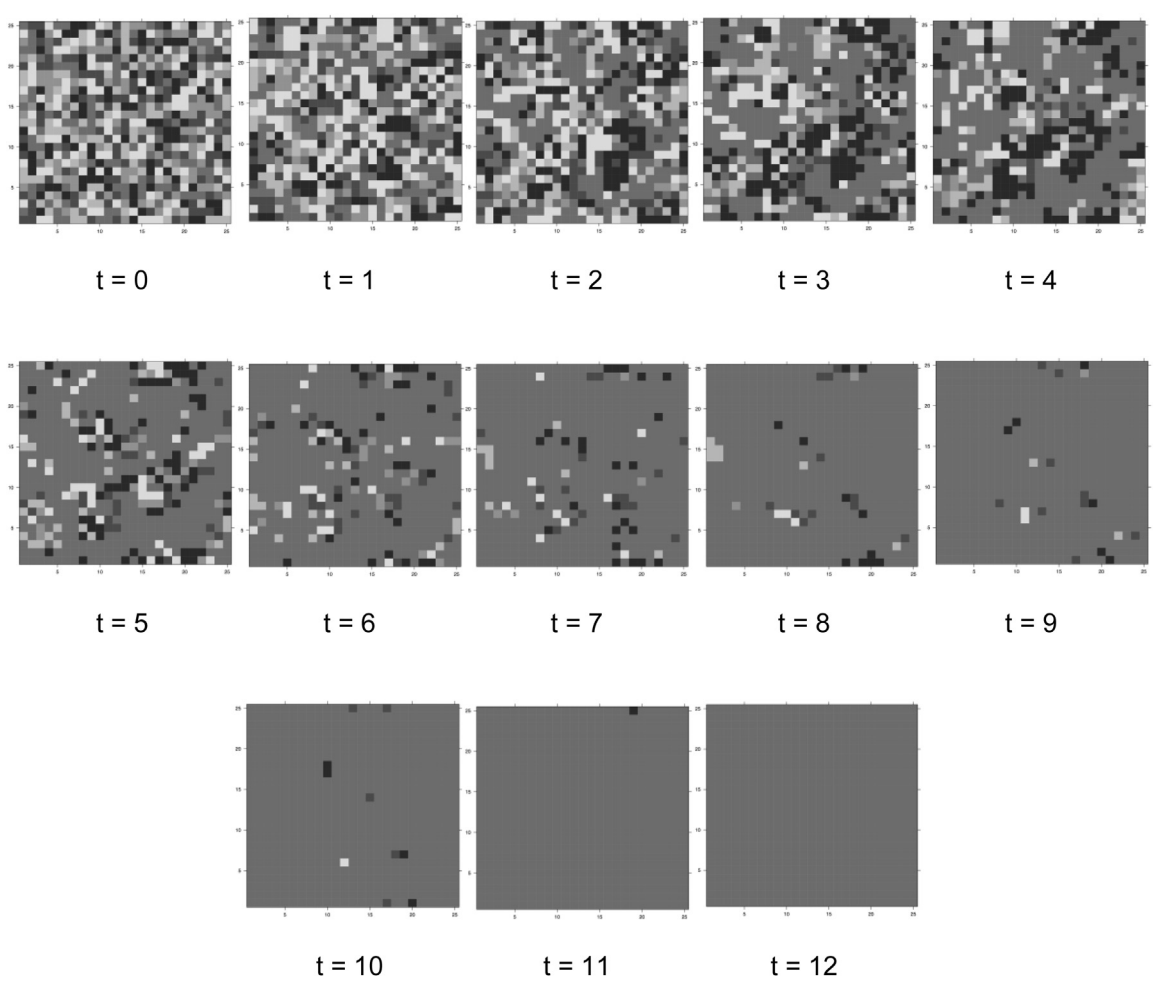


Fig. B2.1. Time series of land uses (each type shown using a different shade of grey) in one run of FEARLUS showing lock-in in twelve steps.

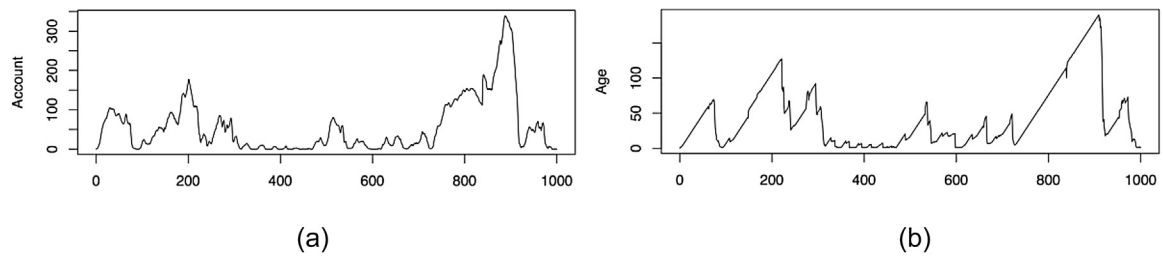


Fig. B2.2. Time series plots of mean wealth ('Account' in the model) (a) and mean age of businesses (b), showing the initial regime lasting around 100 time steps before all agents become bankrupt (indicated by a sudden drop to zero in mean age), followed by another lasting roughly 200 time steps, and then more of various durations. The mass bankruptcy events are precipitated by a relatively prolonged decline in mean wealth.

A situation in which any abnormally large proportion of farmers were going out of business each year would be regarded in the real-world as a shock; but if all of them go bankrupt, that is taking the situation to an extreme, one that in the real world would be unlikely to occur (not least because real farmers are not pure imitators: there is heterogeneity in farmers' willingness to experiment). Land abandonment due to lack of profitability in farming in some parts of the world has been a concern for a number of years (MacDonald et al., 2000). Were we to simulate such a systemic change in full, showing the system restructuring after land abandonment by farmers, we would need to include in the model processes such as urbanisation, 'horsification' (Hatna and Bakker, 2011), afforestation or the return of the land to nature. In other words, the model needs to have in its ontology the concepts needed to represent the new possible system states, and include new algorithms to represent any associated processes (ΔL and ΔP systemic changes). Thus, whilst it is quite possible to improve FEARLUS so that it could handle such a change, if we were to do so, the effect of a mass-bankruptcy event would be to move the system state outside the original FEARLUS system boundary. More precisely, if the new model were called FEARLUS++, then before a mass-bankruptcy event, FEARLUS++ would have states expressible in the vocabulary of FEARLUS; after a mass-bankruptcy event, that would no longer be the case.

based models. The advantage of process-based models, supposedly, is that if we are correctly describing processes then we can predict how systems will behave in the future. This is true if the systems do not change structurally. However in environmental sciences in most cases they do (Milly et al., 2008); especially if the human factor is a part of the system. A modeller needs to keep in mind that SES are complex adaptive systems, constantly changing and featuring nonlinear, self-organizing and out-of-equilibrium dynamics (Arthur et al., 1997; Folke, 2006). Thus, if our models rely only on the past behaviour of the system – which may not contain any period encompassing a systemic change – and do not account for how SES may evolve in the future, we cannot expect that our predictions to be true. This issue also closely relates to the notion of equilibrium. While it may be convenient to conceptualise the existence of a unique equilibrium that delivers Pareto efficient allocation, there may in fact be multiple equilibria or no equilibrium at all. While shifts between multiple equilibria or steady states, particularly in modelling of ecological regime shifts, have been subject of ecological research for several decades (Scheffer et al., 2001), traditional economic – and even environmental economic – models deal with marginal changes around an equilibrium (Stern, 2008). In other words, they are designed to explore marginal changes along a certain point or trend, in many cases reconstructed from historic data. Yet, when focussing on systemic changes in SES – such as social-ecological regime shifts – the emphasis is on exploration of the transient dynamics, which may be at times abrupt (Hughes et al., 2013).

The challenge of change in structure is covered extensively in the works of Beck (2002, 2005; 2009). Beck's discussion of the issue is conceptualised around a classical mechanics representation, but an example using an agent-based model is shown in Box 2. Beck (2002) makes a distinction between 'apparent' and 'true' (evolutionary) structural change. To Beck, apparent structural change is largely a matter of ignorance: a model doesn't contain enough equations to capture all the dynamics in the real world, and its users are 'surprised' when the system behaves in a way the model cannot describe. True structural change (Beck, 2009) is the breakdown and restructuring of a system. The functions modelling the 'before' and 'after' systems have different domain and range, parameters, and links between the states. Using $\boldsymbol{f}^0$ to caricature the 'naïve' system of functions,[2] Beck (2005) contrasts this with $\boldsymbol{f}^1$, a refined function including more phenomena. This is, to Beck, apparent structural change – when $\boldsymbol{f}^0$ was built, there wasn't enough information to build $\boldsymbol{f}^1$; the difference between $\boldsymbol{f}^0$ and $\boldsymbol{f}^1$ is represented in $\boldsymbol{f}^1$ alone by the model being in different subvolumes of state space. Further information and refinements create $\boldsymbol{f}^2$, $\boldsymbol{f}$, and so on; at $\boldsymbol{f}^\infty$ we (never) reach the "truth of the matter" (Beck, 2005, p. 655). However, by induction, arguably all changes on the path to $\boldsymbol{f}^\infty$ are 'apparent', ruling out any 'true' structural change. Beck (2005) would be comfortable with this: in footnote 4 on p. 655, he effectively characterises 'true' systemic change as a change to the dimensionality of the state space over which $\boldsymbol{f}$ operates. Adding new variables to the state space, domain or range of $\boldsymbol{f}$, however, just seems to be reflecting a different form of ignorance from that leading to adding new functions to $\boldsymbol{f}$.

As defined earlier, systemic change can arise from change in structure (ΔL and ΔP) as well as 'significant' change in state (ΔE). Beck's (2002) 'apparent' structural change corresponds closely with ΔP (adding new links in the network of possible state transition functions). 'True' structural change, in Beck's terminology, is more related to what we have called ΔL systemic change. Change in state ΔE would not be structural change under Beck's formalism, but note that it is reflected in $\boldsymbol{f}^1$'s trajectory operating in a superset of the state space that $\boldsymbol{f}^0$ can, which may explain his choice of the term 'apparent' to reflect the ΔP systemic change from $\boldsymbol{f}^0$ to $\boldsymbol{f}^1$. Whilst we agree that ΔL systemic change is more significant, for our purposes, since systemic change is about change in the language used to describe systems, ΔE and ΔP systemic change are no less 'true'. Indeed, the example in Box 2 shows how the presence of ΔE systemic change in a model can suggest a need for ΔP and ΔL.

[2] For convenience, our notation simplifies that used by Beck (2005). We use $\boldsymbol{f}^n$ where he uses $[\boldsymbol{f}^n, \boldsymbol{h}^n]$.

1.3. Subjectivity

As the arguments above suggest, there are unavoidable subjectivities in how systemic changes are understood and explained that will be uncomfortable to traditional scientific thinking. Clearly the language describing a system and the algorithms describing its dynamics are themselves sources of subjectivity. With more knowledge and data, a different language or set of algorithms might have been used that would have accommodated a systemic change. This subjectivity is also closely related to the system boundaries and scales: what may be considered a systemic change in the short term, may revert to the previous dynamics in the long term; what may be seen as dramatic and systemic by one, may be seen as normal and within bounds by another. The temporal perspective on systemic change is considered in more detail by Beck (2005), since one source of the information that leads from $\boldsymbol{f}^0$ to $\boldsymbol{f}^n$ is deeper knowledge of the states the system has had in the past. Subjectivity also arises from the uses to which a model would be put, and given a requirement to fit the recent past and predict to the near future, many modellers would prefer $\boldsymbol{f}^0$ for reasons of parsimony (higher orders of $\boldsymbol{f}$ would be 'overfitting').

Subjectivity with respect to systemic change also has an emotional dimension in that negative connotations may be associated with the immediate aftermath of a shock and those who have suffered from it, but systemic change can also be part of positive transformations (Folke et al., 2010). Examples might include the transition to democratic modes of governance or a shift in consumer preferences to environmentally friendly goods or low-carbon energy sources, though even in these cases, not all will agree they are necessarily changes for the better. The contrast between different perspectives on the same event can be seen in an ecological case: the local extinction of one species presents an opportunity for others. This means that given our inherent loss-aversion (Kahneman, 2011) we will be more likely to pay more attention to modelling the changes that we may see as negative rather than those that we deem as positive, potentially limiting the range of outcomes that could be considered.

1.4. The thematic issue and the rest of this article

Formal models, and especially simulation models, play an essential role in understanding systemic changes in coupled SES. Theoretical and conceptual models (those not necessarily fitted to empirical data) have been fundamental in studying ecological (Carpenter et al., 1999; Gunderson and Holling, 2002) and social-ecological regime shifts[3] (Lade et al., 2013), and in developing early warning signals for approaching regime shifts (Scheffer et al., 2009; Dakos et al., 2015). Theoretical models are instrumental in exploring potential drivers and interventions to achieve desirable future SES states (Biggs et al., 2009; Polasky et al., 2011; Levin et al., 2013). Such exploration is especially vital in the modern interconnected world where regime shifts in SES are often not just a problem for a single region or ecosystem but increasingly become a global common good problem. Advances in data-driven computational models are also being made in studying the emergence of nonlinearities in SES (Vespignani, 2012), but may experience limitations when there are no data on anticipated future states of the system. Given the acknowledged challenges in integrated modelling of coupled SES (Voinov and Shugart, 2013), modelling fundamental changes in their structure may need to push current SES modelling practices beyond the state-of-the-art. This could possibly be achieved by learning from modelling of systemic changes in SES experienced by ancient civilizations (Axtell et al., 2002; Heckbert, 2013), although behavioural sub-models may still need to rely on stylized theory grounded in ethnographic records (Janssen, 2009).

This thematic issue[4] of Environmental Modelling and Software focuses on modelling systemic change in coupled SES. The goal of the thematic issue is to provide a systematic overview on how model design and analysis is (or should be) aimed at representing the processes and consequences of systemic changes in SES, supported by modelling examples. The papers contributing to this thematic issue address questions of model design, and how this needs to be approached differently to cater for systemic change in coupled SES. We attempted to solicit contributions that cover a variety of modelling techniques, and include case studies from diverse geographical regions. It is therefore gratifying that the articles in this thematic issue feature case studies in the "West" as well as the Global South, and in temperate and tropical zones. There is also a variety of modelling approaches, including Bayesian and System Dynamics methods, as well as Agent-Based Modelling.

In this article, we briefly consider the history of modelling systemic change. We then propose a framework summarising what we see as the key points to discuss in modelling systemic change, and use it to introduce the papers in this thematic issue, before concluding with a discussion of our findings.

2. Modelling systemic change: A brief history

Modelling systemic or structural change in socio-environmental systems is not new. In ecology the dominant view that ecosystems are in or developing towards a single global equilibrium was challenged with the discovery of multiple stable states in ecosystems (e.g. Holling, 1973). This has led to a growing body of research investigating the transitions between alternative states (Scheffer et al., 2001). Efforts in analysing systemic change in socio-economic, social and socio-environmental systems are more recent. In the following section we provide a short overview of research on modelling systemic change. Given the scope of this article and the broadness of the issue, which has been addressed in various fields using different names, this overview cannot be comprehensive but aims at representing a few selected major contributions.

2.1. Resilience and regime shifts in ecosystems

The seminal work of Holling (1973) on stability and resilience of ecosystems emphasized the need to move beyond analysing ecological systems as systems with single equilibria towards studying multiple equilibria and the transient dynamics at their boundaries. Systems can self-organize around one of several possible equilibrium points, attractors or stable states. Using simple models of predator–prey interactions, he could show the existence of multiple basins of attraction within each of which ecosystems fluctuate. The resilience of the system then characterizes the

[3] Shifts driven by social-ecological feedbacks, for example a sudden collapse of collective action and resources in a common pool resource.

[4] The idea for this thematic issue began with a session at the bi-annual conference of the International Environmental Modelling and Software Society in 2012 in Leipzig. The original session in Leipzig had ten papers, covering a range of systems from farming to urban shrinkage, and pleasantly surprised by the response, we put out a wider public call in seeking contributions to this issue distributed in modelling communities engaged in SES and resilience research. The iEMSs articles can be accessed on line here: http://www.iemss.org/sites/iemss2012/proceedings.html#H3.%20Modelling%20responses%20to%20shocks%20in%20coupled%20socio-ecological%20systems. Note that not all contributors to that session chose to prepare an article for this issue.

amount of disturbance a system can withstand without crossing into a different basin of attraction. Slow changes in the endogenous processes, which provide resilience, such as stabilizing feedbacks, can make the system vulnerable to random shocks or rare events that can trigger a sudden dramatic change and loss of structural integrity of the system. Since these early works the concept of resilience has been further developed to also explicitly focus on intentional systemic change in SES, i.e. transformation that may be necessary to maintain the overall functioning of a system when conditions change (Folke et al., 2010).

Large, abrupt, persistent changes in the structure and functioning of ecosystems have been called regime shifts (Biggs et al., 2012). A regime shift is a shift of the system from one basin of attraction to another when a critical threshold or tipping point is exceeded. Regime shifts in ecology have often been modelled as bifurcations in dynamical systems and analysed in terms of shifts in dominance of positive (reinforcing) and negative (dampening) feedback loops. An iconic and well-understood example of a regime shift in an ecosystem is the shift of a shallow lake from a clear water state dominated by macrophytes to a turbid state dominated by planktonic algae (Carpenter, 2003; Scheffer, 2009). This shift is caused by nutrient (particularly phosphorus) inflow into the lake from adjacent agricultural areas and untreated sewage water. In the clear water state macrophytes dampen the effect of nutrient inflow by absorbing and trapping excess phosphorous in the water column, which limits the occurrence of algal blooms (negative feedback). Once nutrient levels have passed a certain threshold linked to the absorptive capacity of the macrophytes, they may accumulate in the water column and lead to an increased growth of algae. Increases in nutrient levels can often occur in combination with a disturbance such as a storm. The algae reduce light penetration, which causes the death of the submerged vegetation that stabilizes the sediments, leading to the release of nutrients and further increasing the growth of algae. This amplifying (positive) feedback shifts the lake to a turbid state. Recycling of nutrients from sediments then keeps the system in this alternative state making it very difficult to switch back to the clear water state. It is characteristic of regime shifts that the system state changes very little over a large range of changes in the driver until the system relatively rapidly shifts into the new regime from which it is very hard to move back again – a process also known as hysteresis (Voinov and Tonkikh, 1987). Similar dynamics involving changes in dominant feedbacks have been observed and modelled for instance for grasslands (Anderies et al., 2002; Staver et al., 2011) and coral reefs (Crepin, 2007). In practice, however, determining whether an observed ecosystem change indeed represents a regime shift is often difficult (Crepin et al., 2012).

The management of ecosystems that exhibit regime shifts poses significant challenges because of the nonlinearities and uncertainties involved (Levin et al., 2013). Models that address the optimal management of ecosystems with regime shifts and provide early warning signals that indicate an approaching shift have thus recently received much attention. From an optimal control point of view it is the initial conditions that determine whether it is optimal (in terms of the cost-benefit ratio) to take measures to prevent a regime shift or allow the regime shift to happen. Indeed, there can be situations in which neither state is more optimal than the other (Brock and Starrett, 2003; Crepin, 2007). Analysis of ecological time series data and modelling has laid the ground for the development of early warning signals for approaching regime shifts (Scheffer and Carpenter, 2003; Scheffer et al., 2009). Such warning signals arise because of critical slowing down of the rate of recovery of the system in the vicinity of a threshold (Wissel, 1984). They include for instance rising variance of a system variable (Brock and Carpenter, 2006), increase in autocorrelation (Ives, 1995), skewness (Guttal and Jayaprakash, 2008), spatial correlation (Dakos et al., 2010) and others (Carpenter et al., 2011). Models of regime shifts were instrumental in identifying early warning signals, however, their detection in real systems remains a challenge (Dakos et al., 2015). While early-warning signals could serve as vital determinants of an approaching systemic change, whether or not a regime shift actually occurs depends on the resilience of a system (Biggs et al., 2009).

In another strand of ecological modelling, Jørgensen (1986, 1992) suggested exploring structural dynamics in ecological systems by optimizing parameter values and hence the structure of an ecosystem according to an eco-exergy goal function, which describes the work capacity (work energy) of the ecosystem. Jørgensen (2014) reviews the practice of applying structurally dynamic models to explore the dynamics of lake ecosystems over broad variations in forcing functions, allowing for model adaptation to new conditions. Beck (2005) provides case studies of systems that display substantial, qualitative change in their behaviour and produces an extensive classification of parametric change that may be required to model such systems.

2.2. Systemic change in economic systems

The economic discipline has been studying systemic changes primarily in the context of the response of an economic system to exogenous (for example environmental) shocks, which knock it out of equilibrium, and the costs of returning it back to equilibrium (Higgs, 1986; Eboli et al., 2010; Li et al., 2013). Among early work taking a different approach was that of Baumol and Benhabib (1989) who looked at the nonlinear dynamics of economic systems through the prism of chaos theory, discussing disturbance versus sharp qualitative changes, 'strange attractors', and questioning the reliability of forecasting models. Brock et al. (1991) brought the idea further by exploring nonlinear dynamics in various markets based on chaos theory, and applying both statistical and simulation methods. Around the same time Bak and Chen (1993) applied the concept of self-organised criticality to demonstrate that macro-economic fluctuations may be a result of cumulative impact of many negligible and independent shocks to individual sectors of an economy without any exogenous shock. With an approach originating in physics, Bak and Chen (1993) illustrated that large fluctuations in aggregated economic activity emerge from small sectoral changes due to the presence of local interactions among them and nonlinear assumptions on technology. Anderson et al. (1988) opened a series of books discussing economy as an evolving complex system where nonlinear dynamics is a norm.

Brock (2006) applied a discrete choice model combined with a model of phase transition to study the emergence of tipping points, abrupt changes, bifurcations and hysteresis in social systems. These dynamic processes are the result of endogenous social interactions, which drive the system into various 'traps'. This work is an extension of the economic model with explicit treatment of social interactions by Brock and Durlauf (2001). Lately, this work on examining regime shifts and tipping points in economic time series data was tested in an empirical application with a weak link to an environmental system. In particular, Elser et al. (2014) find statistical evidence for distinct price regimes in key agricultural input commodity markets and critical transitions between them by performing statistical analysis of fertilizer and agricultural food commodities time series.

Most of the recent work on modelling major economic events that are seen as systemic changes is in the domain of pure economic models, not SES. The most recent financial crisis was largely triggered by the fact that economic actors were one-by-one imitating seemingly rational rules (Anand et al., 2013; Johnson and Lux 2011).

Ingram et al. (2012) explore the boom and bust dynamics among firms in an economic agent-based model (ABM) that is subjected to external shocks. Housing bubbles are another example where a collapse in price follows the gradual spread of expectations of receiving a high dividend from investments that exceed more rational valuations (Arce and Lopez-Salido, 2011). The diffusion of dubious investment practices was contagious, leading to a crisis point when the actual values of financial assets were more carefully inspected and caused a major drop in prices. Further, since banks are interconnected, metaphorically forming 'financial ecosystems' similar to ecological food webs (Haldane and May, 2011), one failure triggers a domino effect, leading to high systemic risk. Early warning indicators to predict an upcoming run-on-the-bank (Vakhtina and Wosnitza, 2015) or unfolding financial crises (Quax et al., 2013) are being developed.

Economics also pays some attention to structural changes – i.e. changes in the sectoral composition of an economy and shares of output across them. This is usually rooted in the empirical analyses of sectoral data, e.g. a study on the causes of energy intensity reduction (Mulder and de Groot, 2012). Generally in the economic domain, empirical work was advanced by statistical techniques to identify multiple structural changes and thresholds in (non-SES) macroeconomic time-series data (Bai and Perron, 2003). Other modelling approaches, for example a stock-and-flow model of economic activity and pollution (Winkler, 2005), are also applied to study structural changes in economies with environmental applications.

2.3. Social-ecological regime shifts

Despite growing efforts to study systemic change of SES as truly coupled systems, regime shifts have so far mainly been studied as a "substantial reorganization in the ecological subsystem which can lead to changes in the provision of ecosystem services with significant impacts on human well-being" (Crepin et al., 2012). Some recent work on regime shifts in SES focuses on the social and management implications of ecological regime shifts (e.g. Crepin, 2007). At the same time, however, social processes or social regime shifts can have profound impacts on ecosystems. Vespignani (2012) stresses the importance of social processes – such as opinion dynamics, segregation or evolution of social norms – in the emergence of nonlinear properties of SES including tipping points. Limited attention to the social dimension restricts our ability to predict and avert impending regime shifts, or to effectively navigate where thresholds have been crossed (Hughes et al., 2013). Recent work has started to address this gap with the aim to better understand the role of social structure and processes such as power structures, institutional settings or human adaptive behaviour in ecological regime shifts (Horan et al., 2011; Lade et al., 2015). Lade et al. (2015) for instance show with an empirical model of the Baltic Sea fisheries that social processes influencing the behaviour of fishermen can have significant impact on the development of a regime shift such as the collapse of cod stocks in the Baltic Sea.

Note, however, that we distinguish social-ecological regime shifts from ecological or social regime shifts in SES where shifts in one domain have large impacts on the other. See Walker and Meyers (2004) for an illustration of all possible interactions between social and ecological systems in relation to threshold shifts. Social-ecological regime shifts are regime shifts in which the interactions between the social and ecological systems, such as a positive feedback loop involving parts of both the social and ecological subsystems, causes the SES to switch to the other regime (Crepin et al., 2012). The modelling of a social-ecological regime shift goes beyond studying any one system as a driver (such as nutrient input from agriculture as a driver of an ecological regime shift) to including the two-way interactions that result from human adaptive behaviour in response to ecosystem change. Understanding these feedbacks between social and ecological systems is essential not only to understand how a regime shift comes about but also whether there are opportunities for management responses to prevent tipping into the undesirable regime (Hughes et al., 2013). An empirical example is the study of social-ecological regime shifts in lagoons in India and Vietnam (Nayak et al., 2015).

Lade et al.'s (2013) theoretical analysis demonstrated that embedding social dynamics in an ecological system made regime shifts occur that did not happen when the human factor was modelled exogenously. In their model of a community of harvesters of a common-pool resource, the relative importance of two feedbacks affecting the benefits of defectors proved critical in determining either the maintenance of high co-operation, sustainable resource state or the collapse of co-operation and the loss of the resource. One feedback involved changes in resource productivity and the other involved changes in social pressure from co-operators. Another theoretical model presented by Wiedermann et al. (2015) uses an adaptive networks approach that allows for changes in social network structure resulting from ecological changes to investigate the stability of different equilibria. In the model the imitation process of harvesters in a social network including changes in the social network structure is influenced by the resource state at the respective nodes. Their main finding indicates that the rate of interactions in the social network determines the stability of the prevailing sustainable regime, but also raises questions as to the extent to which the macroscopic description can explain the steep transition between a regime dominated by sustainable harvesting and one dominated by overharvesting.

3. The contributions to this thematic issue

In this section, we develop a framework to discuss the modelling contributions to this thematic issue, drawing on the review of Filatova et al. (2015). After a brief summary of the contributions to this special issue we then apply it to analyse how the different models address systemic change.

3.1. Towards a framework for discussing models of systemic change in socio-environmental systems

The question of the challenges associated with modelling socio-environmental systems discussed briefly above is covered in more detail by Filatova et al. (2015), who conclude their review of the area by noting that differences in modelling approaches and practices means not all authors explicitly discuss the ways their models address relevant modelling challenges, and recommend effort is put into building common terminology across the field. The seven modelling contributions to this thematic issue cover a diverse range of systems using a number of modelling approaches, and in discussing them here, we took the opportunity of developing a framework that enables them to be compared, which could be seen as a means of initiating such a commonality. The framework draws on Filatova et al.'s (2015) four challenges, and adds the modelling approach itself, since we asked the contributing authors to reflect on their experiences with the chosen modelling approach, and on uncertainty accompanying emergence and detection of systemic changes in their models.

The framework is based around a diagram that draws on the US National Science Foundation's conceptualisation in the Dynamics of Coupled Natural and Human Systems (CNH) programme, in which the social and environmental systems are represented as separate

boxes, linked by arrows representing processes that link them and reflexive arrows for dynamics within the social or environmental systems themselves. The general idea of the framework we propose here is to use filled or empty shapes to highlight areas that models give specific attention to.

Feedbacks in the model play an important role in the dynamics of systemic change. In particular, closed-loop linkages between and within the environmental and social subsystems have been argued to play a vital role (Crepin et al., 2012; Lade et al., 2013). In the framework the four arrows representing processes within and linking the social and environmental subsystems are each highlighted in grey if a model has corresponding representations of such processes. (Fig. 1(a).) Parker et al. (2008) discuss modes of linkage between models of subsystems, as Filatova et al. (2015) note. There is a distinction between feedbacks and linkages, in that the former entail a time dimension in which, minimally, a variable at time t is used to compute another at time $t + \delta_1$, which in turn is used to compute the former variable at $t + \delta_1 + \delta_2$ (where δ_1 and δ_2 are not necessarily equal, neither are negative, and at least one is positive). By contrast, a linkage could just mean that output from one submodel is used as the input to another. The framework is not strict about the distinction because not all modelling approaches are dynamic.

The second point of interest is how the systemic change develops. As Filatova et al. (2015) point out, systemic change can be driven exogenously or grow endogenously, gradually or as a sudden shock or disturbance. As shown in Fig. 1(b), for endogenous systemic change, the outer portion of a feedback arrow is highlighted where it plays a role in the development of a systemic change. For exogenous systemic change the two arrows at the top of the diagram are used, and filled whenever there is an exogenous disturbance (gradual or sudden) to one or other subsystem.

Spatial and institutional scales of analysis are also relevant to the modelling of systemic change, and this, and the question of nonlinearities and thresholds within and across subsystems are grouped by Filatova et al. (2015) under the general heading of complexity. In the diagram (Fig. 1(c)), we use the box for each subsystem to record the main entities modelled in that subsystem choosing wording to reflect the scale. Where mention is made of thresholds being crossed in processes operating within a subsystem or in a link between the two as part of the development of a systemic change, the 'S' shape next to the appropriate arrow is filled.

The arrows at the bottom of the diagram are used to show where the systemic change is observed to have occurred (Fig. 1(d)). Filatova et al. (2015) review various methods for detecting systemic change when visual inspection or simple statistical comparison of scenarios is insufficient. One of the arguments in this paper is that systemic change essentially amounts to a change in the vocabulary used to describe the system.

The box in the middle of the diagram is to record the modelling approach. The diagram itself cannot be used to reflect on the modelling approach as such, but the inclusion of a label allows the potential for comparisons to be made given sufficient applications. In the call for papers for this thematic issue, we asked contributors to give consideration to why they adopted the modelling approach they did, what conceptual and modelling challenges they encountered in representing systemic changes using that approach, and how they tackled uncertainty. Were a larger number of papers discussing systemic change reviewed using the framework herein, some of these issues might emerge more clearly by comparing diagrams of different modelling approaches. For example, how often do the models include feedbacks that close the loop between social and environmental systems and/or represent internal dynamics of the social or environmental system? How often do they feature endogenously grown systemic change as opposed to exogenously stimulated?

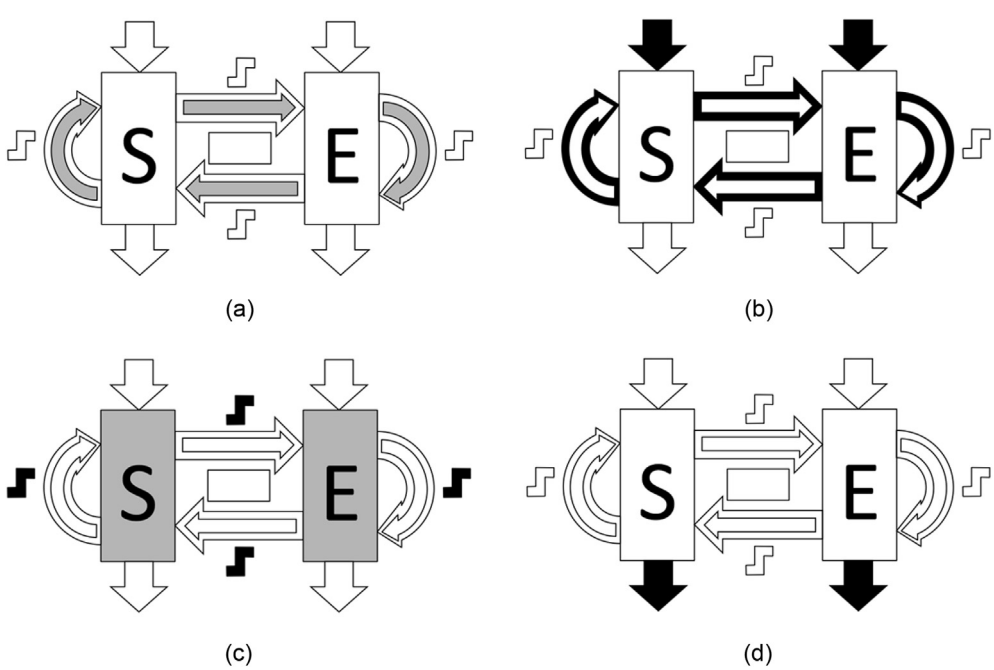


Fig. 1. Areas of the framework diagram used to highlight the four challenges in Filatova et al.'s (2015) review. The social (S) and environmental (E) systems are represented as boxes with (a) the inner arrows showing explicitly represented feedbacks in the model; (b) the outer arrows showing how systemic change develops endogenously, and input arrows at the top how it is influenced by exogenous variables; (c) complexity issues, with scales of entities in the social and environmental subsystems described briefly in the boxes, and nonlinearity in 'S' shapes associated with each endogenous feedback arrow; (d) detection of systemic change in the arrows at the bottom. The central box is used for the modelling approach.

3.2. Summary of the contributions

This thematic issue contains eight papers discussing models to study systemic changes in coupled SES, one of which has effectively already been introduced in Section 3.1. In what follows we first provide a brief overview of the other seven articles, each of which comprises the study of a specific model of systemic change in a coupled socio-environmental system, before evaluating them using the proposed framework.

Sahin et al. (2015) adopt a system dynamics approach to modelling the governance of water supply in South-East Queensland, Australia, having rejected other approaches (including some used by other authors in this issue) as unsuitable (Fig. 2(a)). Changes in the water supply system are driven by exogenous scenarios of population growth, water use per person, whether or not desalination plants augmented the rain-dependent supply from reservoirs and groundwater, and whether or not pricing mechanisms are used to manage demand in times of drought.

By contrast, Ropero et al. (2015) deploy a hybrid Bayesian network approach in their model of the River Adra in southeastern Spain (Andalucia) (Fig. 2(b)). They model the interactions between land use change and the flow of 'blue' and 'green' water – the former referring to rivers and lakes, the latter to the water in the soil that supports agriculture. An aging population and migration feature in the social system, with intensive greenhouse-based agriculture (supplying much of the European market and employing mostly young migrant workers) replacing traditional agriculture. These greenhouses cause a huge change in the water system – using blue rather than green water for production, and in particular affect the availability of water for other (e.g. domestic) purposes.

Kuhn et al. (2015) feature a case study in the Lake Naivasha Basin in Kenya's Rift Valley, exploring the problem of creating an institutional framework that supports efficient use of water in a lake with highly variable levels under natural conditions (Fig. 2(c)). They emphasise the importance of representing transgressions of institutions by agents in the model, coming to the rather stark conclusion that no realistic institution can manage water extraction to bring about a halt to the long-term trend of declining water levels.

In another agent-based model, Manson et al. (2015) study the bottom-up adoption of rotational grazing practices among family farmers in three states bordering the Great Lakes in the USA (Fig. 2(d)). They explore the roles played by different types of social ties, showing how the potential adoption of such practices is sensitive to the structure of the social network and the spatial distribution of farms. In terms of realistic policy options, greater emphasis is placed on the extension agent forming strong ties with the farmers, to give them the confidence (financial and social) to make the transition away from the (currently) more conventional confinement practices.

Rasch et al. (2015) examine the role of the emergence of norms in managing common grazing land, in a case study site in South Africa, showing that the sustainable management of the land is heavily dependent on the agents cooperating by not seeking to have herd sizes that exceed those of others (Fig. 2(e)). Their work also includes an analysis of whether the household data they used in the model could be substituted for random initial distributions of parameters, or homogeneous settings based on averages. Though

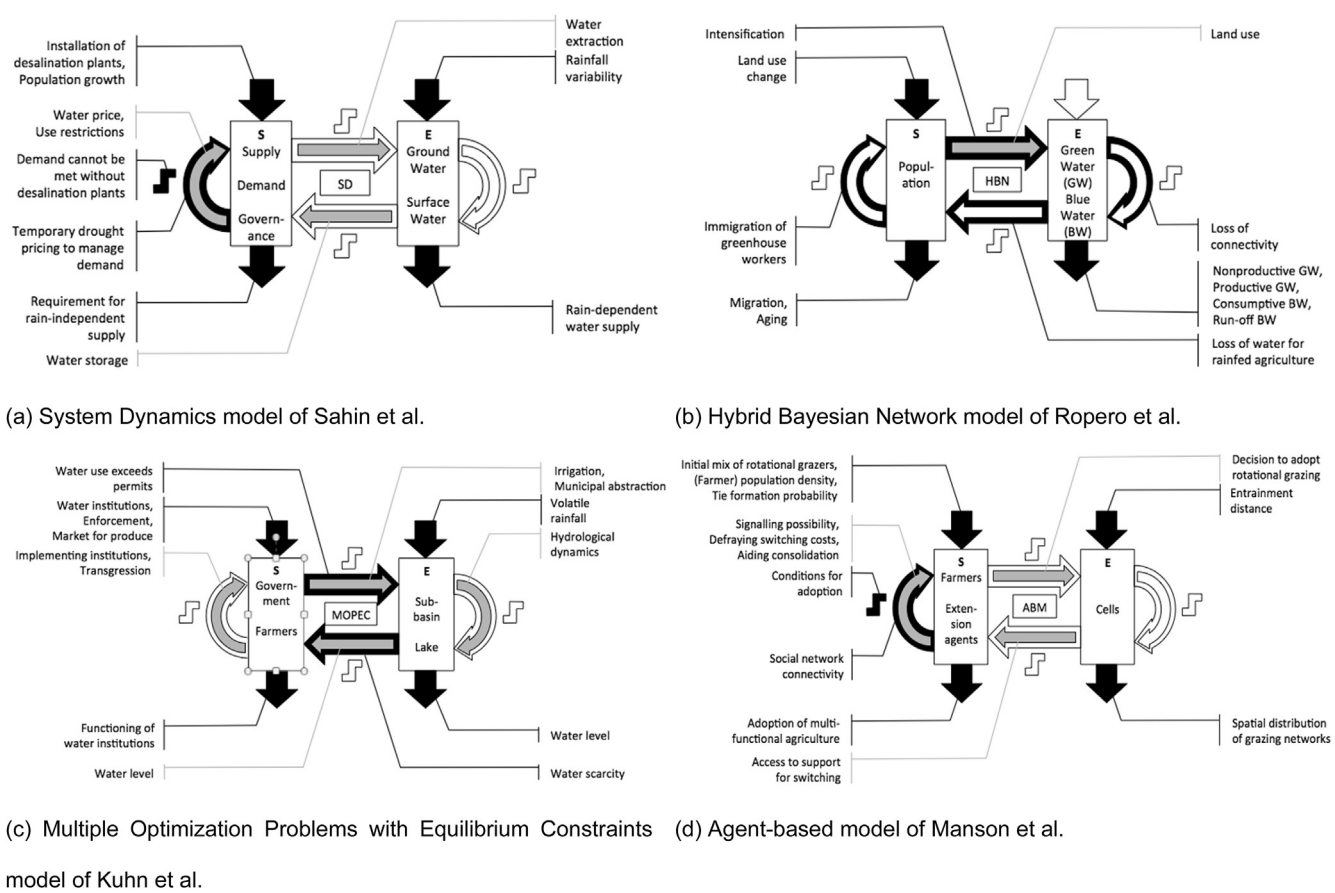
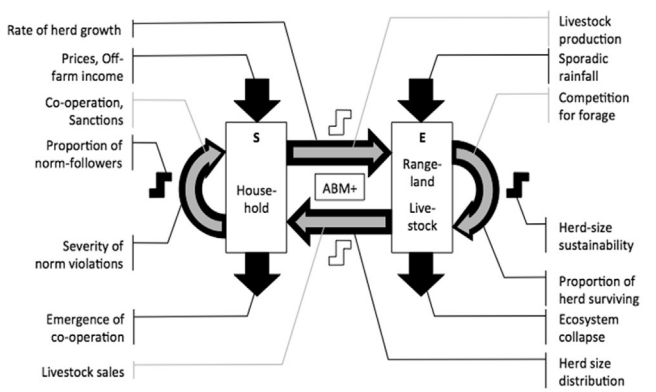
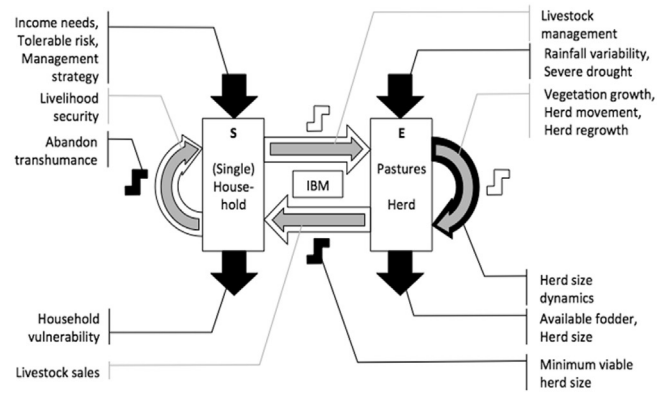


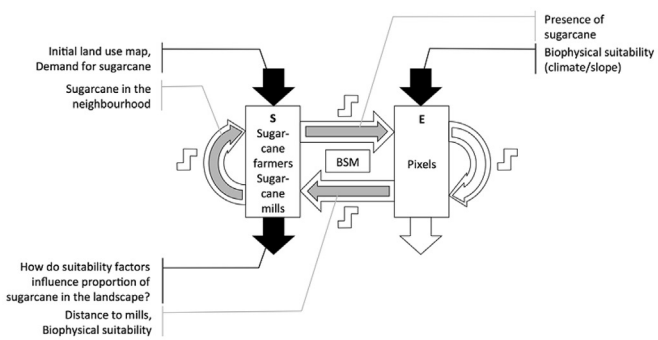
Fig. 2. Applying the framework described in Fig. 1 (and accompanying text in Section 3.1) to the seven modelling contributions to this thematic issue.



(e) Agent-based model of Rasch et al.



(f) Individual-based model of Martin et al.



(g) Bayesian statistical model of Verstegen et al.

Fig. 2. (*continued*).

the structure of the model means that for one of these parameters (initial cooperativeness), using homogeneous settings could never result in an emergence of norms, their results do highlight that in models such as these, path dependence means that the particularities of the case study matter. This finding is consistent with that from Janssen's (2007) reimplementation of the Lansing–Kremer model, which showed that the emergence of temples was conditional on various aspects of the case study in Bali.

Martin et al. (2015) simulate pastoralists in the Atlas mountains of Morocco (Fig. 2(f)). Their work challenges the idea that the transhumant lifestyles of the herders is threatened by drought, as is generally accepted. Other drivers of income variability are also significant, as households supplement their income with wage labour and tourism activities, and there are issues with land availability. Results show that as well as socio-economic and environmental drivers (which could be seen as exogenous), embedded system feedbacks lead to abandonment: oscillations in herd size due to interactions between pasture availability and animal husbandry; and natural variability in rainfall (as opposed to severe drought).

Verstegen et al. (2015) use a statistical model-fitting approach to look for evidence of systemic change in the cane sugar crop land expansion into São Paulo state in Brazil (Fig. 2(g)). They adapt the classical approach of model-fitting assuming that the model parameters are constant over time to one in which parameters are fitted at each step. They use a paired run test to decide whether there is a significant difference between the different models fitted as a result. Though they find that there are significant differences, they are unable to relate the times when the fitted model at one time is different from those at others to known exogenous events expected to cause systemic change. Although there are some issues with parameters being insufficiently determined by the data, the degree to which parameters are determined changes over time. This paper does suggest that systemic change can entail a requirement to rethink the model.

We now turn to more detailed discussion on the contributions of the modelling articles with respect to the framework introduced in Section 3.1.

3.3. Applying the framework to the modelling papers

(i) Feedbacks

Most papers feature feedbacks between the social and environmental systems. For example, Martin et al.'s (2015) model features feedback between herd size and the choice of grazing availability, finding that the oscillation in resource availability and stocking density is responsible for vulnerability of householders to drought rather than severe drought itself being the sole determinant of vulnerability. Rasch et al. (2015), who also model livestock production, feature feedbacks between the social and environmental subsystems, as norm-following influences householders' decisions and the consequences of this for herd sizes and the availability of forage are played out. Kuhn et al. (2015) have a similar approach in the dynamics between the availability of water and decisions to extract it. Ropero et al.'s (2015) paper, however, uses changes in land use as a driving variable with which to evaluate the distributional impact on demographics and water availability. Though it is difficult to argue that their hybrid Bayesian network approach explicitly represents feedbacks, it could be countered that the effects of these feedbacks are captured in the

conditional probability functions over the timescale of analysis.

Interestingly, nearly all the papers represent some sort of internal dynamics in the social system; it is environmental dynamics that are more commonly missing. In Sahin et al.'s (2015) paper, for example, the supply side of the water model does not feature its own internal dynamics other than feeding the surface water inflow through the system. Manson et al. (2015) and Verstegen et al. (2015) have in common that the environmental side largely comprises the space in which the social activity takes place. Nevertheless, in both models, it is the topology that is important in mediating the decisions made in the social side. In the case of Manson et al.'s model, this is the distance over which social ties can meaningfully be maintained to support the transition to rotational grazing; whereas in Verstegen et al.'s case study, distance to mills and sugarcane in the neighbourhood both affect whether sugarcane is predicted to be in a cell.

(ii) Sources of systemic change

The modelling papers in this issue cover two main options for driving systemic change endogenously or exogenously. Kuhn et al. (2015), Ropero et al. (2015) and Verstegen et al. (2015) all use exogenous drivers. In the case of Kuhn et al., the driver is different institutions used to manage the exploitation of the lake's water. For Ropero et al., the driver is a change to farming practices involving an increased use of greenhouses. Here, however, we have also represented the systemic change as endogenous when using the framework (Fig. 2(b)), though one might not expect the arrows to be highlighted in this way unless the corresponding feedback is also highlighted. We took this decision to reflect the point made earlier, that although the feedbacks are not explicitly represented, the associated dynamics embodying a systemic change are supposedly embedded in the conditional probability functions. Verstegen et al. consider a number of exogenous drivers in both the social and environmental subsystems as options for explaining the changes in model parameterisation they observe, including changes in regulations governing sugar-cane production, the financial crisis, and poor harvests suspected to be driven by the weather. However, in the model itself, changes are driven by demand for sugarcane on the social side, and climate and slope on the environmental.

No paper features exclusively endogenously driven changes. In Manson et al. (2015), whether systemic change occurs is a function of endogenously driven social network connectivity enabling the adoption of multifunctional agricultural practices, but the connectivity itself is strongly related to exogenous features of the model (and associated case study), such as population density and tie formation probability. In Rasch et al. (2015), endogenous change is driven by off-farm income and climate, but the emergence of cooperation or ecosystem collapse arises through the endogenous use of norms to regulate the exploitation of a common-pool resource. Similarly, Sahin et al. (2015) and Martin et al. (2015) have a mixture of endogenous and exogenous drivers. Sahin et al. use scenarios featuring assumptions about population growth, demand, water pricing and the use of desalination technology, but endogenously model supply shortages. Martin et al. model a single severe drought as an exogenous driver, but endogenously model the interactions between herd sizes and grazing availability.

The lack of exclusively endogenously-driven systemic change models is largely a question of scale. All models operate at a subnational level, but it would be wrong to draw a boundary around these systems and argue that they are unaffected by processes outside them. Climate change operates at a global level, but features in one way or another as a driver of five of the models. Drivers on the social side are less consistent, but, featuring such things as demographic change, demand and prices, are nonetheless affected by global processes.

(iii) Complexity issues

Kuhn et al. (2015) model at the basin scale, covering the rivers in the Lake Naivasha basin as well as the lake itself over a twenty-year period, and use agents representing user associations and the water management authorities. Ropero et al. (2015) also model at the basin scale. Verstegen et al. (2015) consider the 250,000 km^2 region of São Paulo in their model, also covering a period of twenty years, and choose a spatial resolution that is larger than the mean farm size. A state-level spatial scale is also implicit in Sahin et al.'s (2015) model, though it is not spatially explicit. By contrast, Manson et al. (2015) use a stylised 3600 km^2 space in their model, covering a fifteen-year period and representing individual farmers and extension agents explicitly. Martin et al. (2015) also used a stylised space parameterised to the conditions in their case study, with agents representing herds and households.

Nonlinearities are inherent in ABMs as soon as the algorithms representing their behaviour use if-then-else statements (Izquierdo and Polhill, 2006). Ropero et al. (2015), however, in their Bayesian Network model, use Mixtures of Truncated Exponentials to represent mixtures of discrete and continuous variables. Nonlinear functions also feature in Sahin et al. (2015) water supply model, for example, in desalination plants switching to renewable energy generation when not in use for water production.

Most of papers in this thematic issue do have some input variables that are supposed to have a critical threshold value. For example Kuhn et al. (2015) operates with the threshold values of the water levels in the lake based on the historic data on water scarcity, and use them in the model as policy scenarios within a 'water allocation plan' to decide when to restrict water usage. Manson et al. (2015) endow farmer agents with thresholds that impact how social network ties are formed and how signalling regarding a success in agricultural practice spreads. Agents in Rasch et al.'s (2015) model are endowed with thresholds related to the innovation diffusion submodel.

Yet, systemic changes are measured in the output metrics, usually at macro level. In this respect, we highlight work in three papers. Martin et al. (2015) produce heat maps averaged over 200 simulation runs to visualize the clusters of secure and insecure demand levels for grazing among pastoral households, from which threshold levels of herd size can be estimated. These threshold values vary with scenarios of climate variability and mobility strategy. Rasch et al. (2015) notes that the results are path-dependent with a collapse of SES building up gradually over time. There are several threshold values for the share of cooperators versus defectors of social norms, which serve as the macro metrics capturing the systemic change in Rasch et al.'s model. For example, cooperation always emerges if the share of norm followers reaches 81% and never happens if a critical threshold of 51% norm followers is not passed. These values vary with how heterogeneous agents' attributes coming from empirical data are set up. Ropero et al. (2015) use k-means clustering to identify the threshold values for the tails of probability distributions of water flows, migration rates and ageing. In other words, authors estimated the thresholds for the probability of the extreme values of these variables.

(iv) Detecting systemic change

For several authors herein, the systemic change is detected because the model is designed to simulate a known phenomenon, whether it is demand for water outstripping supply as in Sahin et al. (2015) and Kuhn et al. (2015), the proportion of farmers adopting rotational grazing practices as in Manson et al. (2015), abandonment of the transhumant lifestyle as in Martin et al. (2015), or

collapse of the herd or emergence of norms as in Rasch et al. (2015). Indeed, for those articles featuring exogenously driven shocks, the detection of the systemic change is simply a question of exploring the differing outcomes that these shocks generate, though it is interesting that Martin et al. (2015) observe that the exogenous shocks do not of themselves necessarily drive systemic change, as they argue has been assumed in similar case studies.

The two papers using Bayesian approaches (Ropero et al., 2015; Verstegen et al., 2015) both take a different angle on shock detection, through looking for the signatures of systemic change in the posterior distributions of their model parameters, with Verstegen et al. also checking how these distributions are affected by time. What is of particular interest in the latter case is that the authors are aware of a number of exogenous shocks to the sugar-cane system that could potentially cause the systemic change they detect, but find themselves unable to specifically relate their observations to any one of them. This may be because their case study has featured a number of disturbances in a relatively short period of time. Among the potentially interesting speculations Verstegen et al.'s observation leads to is the degree to which shocks of one form or another to a system may be seen as 'unusual' or 'rare'. Whether a feature of the subjectivity determining system boundary or not, if disturbances from outside the system are common events, this reinforces the points made earlier about the irrelevance of equilibria in discussing the dynamics of systems.

(v) Reflection on the modelling approach

Most of the papers in this issue have used agent-based modelling in one form or another. The justification for this given by those authors who have considered the matter is largely based on the explicit representation of individual decision-making, with Kuhn et al. (2015) arguing that decisions about water extraction are made individually rather than by the basin society as a whole. Manson et al. (2015) also base their choice on the need to explore social network structure. However, Sahin et al. (2015) article gives explicit consideration to which of agent-based or system dynamics approaches are better suited to their case study, favouring the latter due largely to considerations of time. ABMs are discrete event models, whereas system dynamics models can operate both in discrete and continuous time. When simulating the dynamics of systemic change, the outcomes might depend critically on how the impact of the shock plays out, suggesting that modellers may need to consider finer temporal resolution during these periods. Sahin et al. also note a preference for simulation-based approaches over Bayesian, arguing that the former are better suited to complex problems. However, Ropero et al. (2015) counter that using hybrid Bayesian networks, they are able to compute the propagation of the effects of exogenous shocks to all variables.

The authors point to a number of significant challenges in their discussions, most of which in some way or another relate to uncertainty, which Sahin et al. (2015) attempted to address both by a participatory approach in which stakeholders and experts were involved in the model design and scenario development, and through sensitivity analysis. Parameter sweeps are used to handle uncertainty in all the other papers too (assuming, for the benefit of the Bayesian contributions, that computing the posterior can be seen as activity akin to performing parameter sweeps); in so doing, Manson et al. (2015) refer to challenges they faced in visualising and analysing all the different settings of the model.

Rasch et al. (2015) note challenges with validation due in part to a lack of data. Although this appears to have been due to institutional issues in their case study, if we do not have a fatalistic view of the way in which events unfold in response to shocks, the range of possible outcomes indicated by the model is difficult to validate against the single outcome that occurred historically. If the outcome that did occur is within the envelope of modelled outcomes, perhaps we might feel reassured, but if it did not, whilst the obvious conclusion might be that a model is inadequate in some way, there is also the possibility that the situation is telling us something very interesting about the highly contingent nature of the history of the event itself. Verstegen et al. (2015) also faced issues with lack of data in that their use of the runs test to detect systemic change proved unsuitable when the parameters of the model are ill-defined in the posterior using the available data.

4. Discussion and concluding remarks

Modelling the co-evolving dynamics of complex coupled SES to anticipate the potential outcomes of exogenous shocks, or to study the emergence of endogenous systemic change therein, is ambitious. The most serious challenge in modelling systemic changes in SES concerns the restructuring of a model that may be required if a system it represents experiences a systemic change (Beck, 2005). Contemporary models based on systems of differential or difference equations and dynamical systems theory primarily focus on a change in values of parameters and the strength of feedbacks (equations) that keep the system within one domain of attraction or push it into the other. Other approaches focus on an adaptive or evolving structure of dynamical system models where parameters are not fixed at calibrated values but adjust to maximize a certain exergy objective function (Jorgensen, 2014). Yet, no new unexpected state variables or feedbacks occur in these models, and there is no scope for such a model to generate new equations.[5] However, if the implications of Verstegen et al.'s (2015) work are taken seriously, the model's ontology itself may have to adjust after the systemic change has taken place.

Indeed, enthusiasts of post-modern theorists, in the unlikely event they were ever to cast a critical eye over work such as that presented in this special issue, might well gain mileage applying Lyotard's (1988) *différend*. As described in his book, the *différend* is a situation in which the victim of a crime is deprived of the means to express the wrong done to them using the language of the legal system in which the case is tried. It could be used as a metaphor for the situation a model might find itself in after a significant systemic change, in which the vocabulary of the model is no longer adequate to describe what is happening in the system.

Of course, such enthusiasts might raise similar objections to the very idea of formal modelling in the first place: computer programming languages, systems of equations and probability distributions simply cannot do justice to the nuanced political complexities of environmentally-embedded human societies. Helmreich's (1999) reaction to Lansing and Kremer's (1993) Balinese water temple model is illustrative, whether or not he is an enthusiast of Lyotard. However, the project of modelling is surely based on the hope that formal reasoning and analysis of the knowledge and data we have about SES can be done without relying entirely on the known distortions of human cognition.[6] Nevertheless, if we are to model systemic change in SES without

[5] Adjustment of equations, in principle, can be reduced to a parameter change. Assuming that certain parameters can adopt values corresponding to identity transformations, certain parts of an equation or whole equations can be switched off. In such an approach, all equations representing any potential dynamics still have to be assumed during model design rather than 'evolving' during the course of the model itself.

[6] Though it is argued (Haselton et al., 2005) that humans have adapted to reason well in these systems.

hubris, more humility will be required of us than is already the case for SES themselves.

Since it concerns the ontology of the model, one of the questions we were interested in was whether modelling systemic change had required contributors to change their thinking about system boundary. In the papers in this issue, the structure of the model has mostly been determined by the question it was built to ask, or by the case study narrative. It is thus not immediately clear whether simulating systemic change has, per se, had any effect on what should or should not be modelled, and whether those phenomena that are included are endogenous or exogenous, since the case study and/or research question driving model boundary decisions is associated with systemic change. Sahin et al. (2015), however, argue that it has been necessary to endogenise all aspects of the water supply system, including suppliers, users and infrastructure, in contrast to standard approaches, which treat one or more of these as exogenous. The example in Box 2 also shows how the existence of lock-in states within the system creates pressure to extend the ontology. Verstegen et al. (2015), rather than changing the system boundary, have changed the analytical approach.

Another question pertained to issues of spatial and temporal scale. It is not unreasonable to ask whether, during transition periods or as shocks unfold, models ought to operate at finer spatial or temporal resolutions during these 'critical' periods because of the acknowledged path dependence of observed outcomes (Rasch et al., 2015). This is something none of the papers in this issue do. However, Sahin et al. (2015) give time some consideration in evaluating which of system dynamics and agent-based modelling approaches is better suited for the purposes of studying their case study, pointing out that system dynamics can operate with hybrid continuous and discrete processes.

For all these misgivings, as the work presented here demonstrates, in each of the microworlds studied, interesting findings pertaining to systemic changes therein can be ascertained by allowing the machinery of the model to run its course, whether it is determining the circumstances under which adoption of more sustainable agricultural practices could occur from the bottom-up (Manson et al. 2015), challenging generally accepted theories of the vulnerabilities of pastoralists to drought (Martin et al., 2015), or finding that reversing the long-term trend of declining water levels in Lake Naivasha cannot rely on institutions based on fines for misuse (Kuhn et al. 2015).

None of the authors shirk the issue of uncertainty in so doing, addressing it in a variety of ways as discussed above, but most typically by making thorough explorations of parameter space, and (where models involve stochasticity) using multiple runs of the model for each parameter setting to sample the distributions of outcomes. Articles using Bayesian approaches (Ropero et al., 2015; Verstegen et al., 2015) are particularly strong in this area, in that uncertainty underpins the method: model outcomes are reported as posterior distributions, the only constraint being the number of samples of these that can feasibly be computed when the distributions cannot be derived analytically. The ever-increasing availability of computing power makes this, and other forms of computational modelling more and more feasible, to the extent that work that once seemed impossible can now be given consideration.

This introduction to the thematic issue has been concerned primarily with how modelling systemic change in SES affects the ontology of a model and the approach used to building it. We have demonstrated with an example in Box 2 how models not intended to be applied to systemic change can nevertheless enter states that can be understood as representing systemic change that demand extensions to the ontology to handle the situation better. The examples in this thematic issue are intended to be applied to systemic changes, and though this has affected what has been included in the model, none of the modelling formalisms used allow the representation of unanticipated changes in structure (the most radical of ΔL systemic changes discussed above).

The increasing use of complexity science tools – ABMs, networks, statistical mechanics, which are largely rule-based – in social and ecological domains may potentially open possibilities to include rules that would write new rules as a system at hand restructures. ABMs, and, more recently, adaptive networks are methods with a large potential for modelling structural change. For instance, adaptive networks combine network approaches with dynamical system theory. They allow for the emergence of new network structure through adaptive changes in links and nodes. The approach is similar to ABMs but with the added value of being simple enough to be analysed mathematically.

At the same time, as complexity penetrates in modelling efforts, certain inherent features of the description of regime shifts need to be revised. In particular, in non-stochastic dynamical system models a threshold or a tipping point is usually indeed a point, i.e. a certain parameter value, which if exceeded shifts the system into a different state. In complexity science tools tipping points or thresholds occur at specific points or parameter values only with a certain probability due to randomness inherited in the model's structure. Qualitatively different dynamics may occur in such a model under the same set of parameters in an ABM where bistability regions appear when the equation-based model would indicate a threshold (Tavoni et al., 2012). In these cases we should rather talk about *tipping intervals*. Technically speaking, something similar could also be the case in dynamical system models if we account for parametric uncertainty and realize that all parameters are in fact measured only with a certain degree of accuracy or if we are dealing with stochastic dynamical systems models where the noise could represent either variability in external drivers or internal variability in processes. However this has been rarely done, with the likely exception of fuzzy models.

Accounting for systemic change in modelling SES can easily make models more complex and thus harder to analyse and communicate. Providing for optimization in dynamical systems models, or for learning, adaptation, self-replication and goal-seeking in ABMs for instance results in additional modules and functions in the model. Most importantly a modeller needs to decide whether (i) to build in possible new system states from the beginning and allow the model to choose one of the possible trajectories of future development, or (ii) to include change mechanisms that allow the system to evolve endogenously, possibly with the use of artificial intelligence learning techniques, e.g. genetic or 'memetic' algorithms (Fromm, 2004).[7] In both cases these assumptions have to be made without necessarily knowing what these possible future states or change mechanisms are. They will therefore necessarily be based on assumptions derived from our understanding of past changes, particularly of systems that underwent systemic change, and be limited in the extent to which they can take into account how the system may evolve in the future. These models will therefore largely remain tools to improve our understanding of the possibilities rather than predictive tools.

Just as Janssen (2009) observed about modelling systemic changes in SES with ancient civilizations, despite significant progress in modelling systemic change (see Section 2), it may still be considered an area in its infancy. To summarize: there are several potentially interesting areas of future work, not least revising the modelling ontology, modelling the boundary between two

[7] Though memetics has been criticised by Edmonds (2005) memetic algorithms are still an active area of research – e.g. Springer's Memetic Computing journal.

alternative states as a tipping interval rather than a point, and developing the techniques such as allowing programs to write themselves that would enable more radical explorations of the outcomes of systemic changes than is currently possible. More prosaic, but nonetheless important, is encouraging dialogue among the various disciplines addressing the modelling of systemic change, and we have proposed a framework that we hope may facilitate such a dialogue. Other areas of future endeavour include more rigorous reporting on the justifications for and provenance of the model ontology, and developing methods in the social sciences such as backcasting (Robinson, 2003) for engaging with actors, stakeholders and policymakers to develop systemic change scenarios that are sufficiently detailed to be suitable for exploring with models.

Oreskes et al.'s (1994) arguments about the impossibility of validation of models in open systems have considerably greater force when considering systemic change. This is not to avoid the issue of validation altogether, just that the methods will be different from traditional models: expert validation (Smajgl and Bohensky, 2013) and pattern-oriented modelling (Grimm et al., 2005) being possible options. Modelling still has value in allowing us to explore possible futures ensuring that the logical consequences of our assumptions and knowledge are consistently treated; and in so doing, forcing us to ask new questions of the empirical world. It is the latter that brings us back to the issue of subjectivity raised in the introduction. We usually talk about modelling systems as if 'the system' is an objective reality. Arguably it is not. A system is already some conceptual or mental model that we build carving out a portion of that reality and presenting it in a specific way to suit our purposes. Systemic change may therefore be as much about changes in conceptualisation and understanding as it is about stock market crashes, political revolutions, technological change and mass extinctions.

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References

Anand, K., Kirman, A., Marsili, M., 2013. Epidemics of rules, rational negligence and market crashes. Eur. J. Finance 19 (5), 438–447. http://dx.doi.org/10.1080/1351847X.2011.601872.
Anderies, J.M., Janssen, M.A., Walker, B.H., 2002. Grazing management, resilience, and the dynamics of a fire-driven rangeland system. Ecosystems 5 (1), 23–44.
Anderson, P.W., Arrow, K., Pines, D., 1988. The Economy as an Evolving Complex System. Addison-Wesley.
Arce, O., Lopez-Salido, D., 2011. Housing bubbles. Am. Econ. J. Macroecon. 3 (1), 212–241.
Arthur, W.B., Durlauf, S.N., Lane, D., 1997. The Economy as an Evolving Complex System II. Santa Fe Institute Studies in the Science of Complexity, vol. XXVII. Addison-Wesley.
Axtell, R.L., Epstein, J.M., Dean, J.S., Gumerman, G.J., Swedlund, A.C., Harburger, J., Chakravarty, S., Hammond, R., Parker, J., Parker, M., 2002. Population growth and collapse in a multiagent model of the Kayenta Anasazi in Long House Valley. Proc. Natl. Acad. Sci. U. S. A. 99 (Suppl. 3), 7275–7279.
Bai, J., Perron, P., 2003. Computation and analysis of multiple structural change models. J. Appl. Econ. 18 (1), 1–22.
Bak, P., Chen, K., 1993. Aggregate fluctuations from independent sectoral shocks: self-organized criticality in a model of production and inventory dynamics. Ric. Econ. 47, 3–30.
Baumol, W.J., Benhabib, J., 1989. Chaos: significance, mechanism, and economic applications. J. Econ. Perspect. 3 (1), 77–105.
Beck, M.B., 2002. In: Beck, M.B. (Ed.), Structural Change: A Definition. Environmental Foresight and Models: A Manifesto. Elsevier Science Ltd, Oxford, UK, pp. 51–60.
Beck, M.B., 2005. Environmental foresight and structural change. Environ. Model. Softw. 20, 651–670.
Beck, M.B., 2009. Grand Challenges of the Future for Environmental Modeling. In the Setting of NSF's Environmental Observatories Initiatives. University of Georgia, Georgia: USA, p. 155.
Berkes, F., Folke, C., 1998. Linking Social and Ecological Systems. Cambridge University Press, Cambridge, UK.
Biggs, R., Blenckner, T., Folke, C., Gordon, L., Norström, A., Nyström, M., Peterson, G.D., 2012. In: Hastings, A., Gross, L. (Eds.), Regime Shifts. Encyclopedia of Theoretical Ecology. University of California Press, Ewing, NJ, USA.
Biggs, R., Carpenter, S.R., Brock, W.A., 2009. Turning back from the brink: detecting an impending regime shift in time to avert it. Proc. Natl. Acad. Sci. U. S. A. 106 (3), 826–831.
Biggs, R., Schluter, M., Schoon, M., 2015. Principles for Building Resilience: Sustaining Ecosystem Services in Social-ecological Systems. Cambridge University Press.
Brock, W.A., 2006. In: Repetto, R., Speth, J.G. (Eds.), Tipping Points, Abrupt Opinion Changes, and Punctuated Policy Change. Punctuated Equilibrium and the Dynamics of U.S. Environmental Policy. Yale University Press, pp. 47–77.
Brock, W.A., Carpenter, S.R., 2006. Variance as a leading indicator of regime shift in ecosystem services. Ecol. Soc. 11 (2).
Brock, W.A., Durlauf, S.N., 2001. Discrete choice with social interactions. Rev. Econ. Stud. 68 (2), 235–260.
Brock, W.A., Hsieh, D., LeBaron, B., 1991. Nonlinear Dynamics, Chaos, and Instability: Statistical Theory and Economic Evidence. MIT Press, Cambridge.
Brock, W.A., Starrett, D., 2003. Managing systems with non-convex positive feedback. Environ. Resour. Econ. 26 (4), 575–602.
Carpenter, S., Cole, J., Pace, M., Batt, R., Brock, W., Cline, T., Coloso, J., Hodgson, J., Kitchell, J., Seekell, D., 2011. Early warnings of regime shifts: a whole-ecosystem experiment. Science 332 (6033), 1079–1082.
Carpenter, S.R., 2003. Regime Shifts in Lake Ecosystems: Pattern and Variation. International Ecology Institute, Oldendorf/Luhe Germany.
Carpenter, S.R., Ludwig, D., Brock, W.A., 1999. Management of eutrophication for lakes subject to potentially irreversible change. Ecol. Appl. 9 (3), 751–771.
Crepin, A.S., 2007. Using fast and slow processes to manage resources with thresholds. Environ. Resour. Econ. 36 (2), 191–213.
Crepin, A.S., Biggs, R., Polasky, S., Troell, M., de Zeeuw, A., 2012. Regime shifts and management. Ecol. Econ. 84, 15–22.
Dakos, V., Carpenter, S.R., van Nes, E.H., Scheffer, M., 2015. Resilience indicators: prospects and limitations for early warnings of regime shifts. Philos. Trans. R. Soc. B Biol. Sci. 370 (1659).
Dakos, V., van Nes, E.H., Donangelo, R., Fort, H., Scheffer, M., 2010. Spatial correlation as leading indicator of catastrophic shifts. Theor. Ecol. 3 (3), 163–174.
Eboli, F., Parrado, R., Roson, R., 2010. Climate-change feedback on economic growth: explorations with a dynamic general equilibrium model. Environ. Dev. Econ. 15 (5), 515–533.
Edmonds, B., 2005. The revealed poverty of the gene-meme analogy – why memetics per se has failed to produce substantive results. J. Memet. Evol. Models Inf. Transm. 9.
Elser, J.J., Elser, T.J., Carpenter, S.R., Brock, W.A., 2014. Regime shift in fertilizer commodities indicates more turbulence ahead for food security. Plos One 9 (5).
Filatova, T., Polhill, J.G., van Ewijk, S., 2015. Regime shifts in coupled socio-environmental systems: review of modelling challenges and approaches. Environ. Model. Softw. 75, 333–347. http://dx.doi.org/10.1016/j.envsoft.2015.04.003.
Folke, C., 2006. Resilience: the emergence of a perspective for social-ecological systems analyses. Glob. Environ. Change Hum. Policy Dimens. 16 (3), 253–267.
Folke, C., Carpenter, S.R., Walker, B., Scheffer, M., Chapin, T., Rockstrom, J., 2010. Resilience thinking: integrating resilience, adaptability and transformability. Ecol. Soc. 15 (4).
Fromm, J., 2004. The Emergence of Complexity. Kassel University Press GmbH, Kassel, Germany.
Gotts, N.M., Polhill, J.G., 2010. Size Matters: large-scale replications of experiments with fearlus. Adv. Complex Syst. 13 (4), 453–467.
Gotts, N.M., Polhill, J.G., Law, A.N.R., 2003. Aspiration levels in a land use simulation. Cybern. Syst. 34 (8), 663–683.
Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W.M., Railsback, S.F., Thulke, H.H., Weiner, J., Wiegand, T., DeAngelis, D.L., 2005. Pattern-oriented modeling of agent-based complex systems: lessons from ecology. Science 310 (5750), 987–991.
Gunderson, L.H., Holling, C.S., 2002. Panarchy: Understanding Transformations in Human and Natural Systems. Island Press, Washington, D.C.
Guttal, V., Jayaprakash, C., 2008. Changing skewness: an early warning signal of regime shifts in ecosystems. Ecol. Lett. 11 (5), 450–460.
Haldane, A.G., May, R.M., 2011. Systemic risk in banking ecosystems. Nature 469 (7330), 351–355.
Haselton, M.G., Nettle, D., Andrews, P.W., 2005. In: Buss, D.M. (Ed.), The Evolution of

Cognitive Bias. The Handbook of Evolutionary Psychology. John Wiley & Sons Inc, Hoboken, NJ, USA, pp. 724–746.
Hatna, E., Bakker, M.M., 2011. Abandonment and expansion of arable land in Europe. Ecosystems 14 (5), 720–731.
Heckbert, S., 2013. MayaSim: an agent-based model of the ancient maya social-ecological system. J. Artif. Soc. Soc. Simul. 16 (4), 11. http://jasss.soc.surrey.ac.uk/16/14/11.html.
Helmreich, S., 1999. Digitizing 'development': balinese water temples, complexity and the politics of simulation. Crit. Anthropol. 19 (3), 249–265.
Higgs, P.J., 1986. Australian mining and the economy - a general equilibrium-analysis. Resour. Policy 12 (2), 117–132.
Holling, C.S., 1973. Resilience and stability of ecological systems. Annu. Rev. Ecol. Syst. 4, 1–23.
Horan, R.D., Fenichel, E.P., Drury, K.L.S., Lodge, D.M., 2011. Managing ecological thresholds in coupled environmental-human systems. Proc. Natl. Acad. Sci. U. S. A. 108, 7333–7338.
Hughes, T.P., Linares, C., Dakos, V., van de Leemput, I.A., van Nes, E.H., 2013. Living dangerously on borrowed time during slow, unrecognized regime shifts. Trends Ecol. Evol. 28 (3), 149–155.
Ingram, D., Taylor, P., Thompson, M., 2012. Surprise, surprise: from neoclassical economics to e-life. Austin Bull. 42 (2), 389–411.
Ives, A.R., 1995. Measuring resilience in stochastic-systems. Ecol. Monogr. 65 (2), 217–233.
Izquierdo, L.R., Polhill, J.G., 2006. Is your model susceptible to floating-point errors? Jasss J. Artif. Soc. Soc. Simul. 9 (4).
Janssen, M.A., 2007. Coordination in irrigation systems: an analysis of the Lansing-Kremer model of Bali. Agric. Syst. 93 (1–3), 170–190.
Janssen, M.A., 2009. Understanding artificial anasazi. Jasss J. Artif. Soc. Soc. Simul. 12 (4), A244–A260.
Johnson, N., Lux, T., 2011. Financial systems: ecology and economics. Nature 469, 302–303. http://dx.doi.org/10.1038/469302a.
Jorgensen, S.E., 1986. Structural dynamic model. Ecol. Model. 31 (1–4), 1–9.
Jorgensen, S.E., 1992. Development of models able to account for changes in species composition. Ecol. Model. 62 (1–3), 195–208.
Jorgensen, S.E., 2014. Chapter 2 – structurally dynamic models of lakes. Dev. Environ. Model. 26, 9–34.
Kahneman, D., 2011. Thinking, Fast and Slow. Farrar, Straus and Giroux, New York.
Kuhn, A., Britz, W., Willy, D.K., van Oel, P., 2015. Simulating the viability of water institutions under volatile rainfall conditions – the case of the Lake Naivasha Basin. Environ. Model. Softw. 75, 373–387. http://dx.doi.org/10.1016/j.envsoft.2014.08.021.
Lade, S.J., Niiranen, S., Hentati-Sundberg, J., Blenckner, T., Boonstra, W.J., Orach, K., Quaas, M., Österblom, H., Schlüter, M., 2015. Social dynamics matter for ecosystem regime shifts. Proc. Natl. Acad. Sci. 112 (35), 11120–11125.
Lade, S.J., Tavoni, A., Levin, S.A., Schluter, M., 2013. Regime shifts in a social-ecological system. Theor. Ecol. 6 (3), 359–372.
Lansing, J.S., Kremer, J.N., 1993. Emergent properties of balinese water temple networks - coadaptation on a rugged fitness landscape. Am. Anthropol. 95 (1), 97–114.
Levin, S., Xepapadeas, T., Crepin, A.S., Norberg, J., De Zeeuw, A., Folke, C., Hughes, T., Arrow, K., Barrett, S., Daily, G., Ehrlich, P., Kautsky, N., Maler, K.G., Polasky, S., Troell, M., Vincent, J.R., Walker, B., 2013. Social-ecological systems as complex adaptive systems: modeling and policy implications. Environ. Dev. Econ. 18 (2), 111–132.
Li, J., Crawford-Brown, D., Syddall, M., Guan, D.B., 2013. Modeling imbalanced economic recovery following a natural disaster using input-output analysis. Risk Anal. 33 (10), 1908–1923.
Lyotard, J.-F., 1988. The Differend: Phrases in Dispute. Translated by George Van Den Abbeele. University of Minnesota Press, Minneapolis, USA.
MacDonald, D., Crabtree, J.R., Wiesinger, G., Dax, T., Stamou, N., Fleury, P., Lazpita, J.G., Gibon, A., 2000. Agricultural abandonment in mountain areas of Europe: environmental consequences and policy response. J. Environ. Manag. 59 (1), 47–69.
Manson, S.M., Jordan, N.R., Nelson, K.C., Brummel, R.F., 2015. Modeling the effect of social networks on adoption of multifunctional agriculture. Environ. Model. Softw. 75, 388–401. http://dx.doi.org/10.1016/j.envsoft.2014.09.015.
Martin, R., Linstädter, A., Frank, K., Müller, B., 2015. Livelihood security in face of drought – Assessing the vulnerability of pastoral households. Environ. Model. Softw. 75, 414–423. http://dx.doi.org/10.1016/j.envsoft.2014.10.012.
Milly, P.C.D., Betancourt, J., Falkenmark, M., Hirsch, R.M., Kundzewicz, Z.W., Lettenmaier, D.P., Stouffer, R.J., 2008. Climate change - Stationarity is dead: whither water management? Science 319 (5863), 573–574.
Mulder, P., de Groot, H.L.F., 2012. Structural change and convergence of energy intensity across OECD countries, 1970-2005. Energy Econ. 34 (6), 1910–1921.
Nayak, P.K., Armitage, D., Andrachuk, M., 2015. Power and politics of social–ecological regime shifts in the Chilika lagoon, India and Tam Giang lagoon, Vietnam. Reg. Environ. Change. http://dx.doi.org/10.1007/s10113-015-0775-4.
Oreskes, N., Shrader-Frechette, K., Belitz, K., 1994. Verification, validation, and confirmation of numerical models in the earth sciences. Science 263 (5147), 641–646.
Parker, D.C., Hessl, A., Davis, S.C., 2008. Complexity, land-use modeling, and the human dimension: fundamental challenges for mapping unknown outcome spaces. Geoforum 39, 789–804.
Polasky, S., de Zeeuw, A., Wagener, F., 2011. Optimal management with potential regime shifts. J. Environ. Econ. Manag. 62 (2), 229–240.
Polhill, J.G., Gotts, N.M., Law, A.N.R., 2001. Imitative versus nonimitative strategies in a land-use simulation. Cybern. Syst. 32 (1–2), 285–307.
Quax, R., Kandhai, D., Sloot, P.M.A., 2013. Information dissipation as an early-warning signal for the Lehman Brothers collapse in financial time series. Sci. Rep. 3.
Rasch, S., Heckelei, T., Oomen, R., Naumann, C., 2015. Cooperation and collapse in a communal livestock production SES model – a case from South Africa. Environ. Model. Softw. 75, 402–413. http://dx.doi.org/10.1016/j.envsoft.2014.12.008.
Robinson, J., 2003. Future subjunctive: backcasting as social learning. Futures 35 (8), 839–856.
Ropero, R.F., Rumí, R., Aguiler, P.A., 2015. Modelling uncertainty in social–natural interactions. Environ. Model. Softw. 75, 362–372. http://dx.doi.org/10.1016/j.envsoft.2014.07.008.
Sahin, O., Siems, R.S., Stewart, R.A., Porter, M.G., 2015. Paradigm shift to enhanced water supply planning through augmented grids, scarcity pricing and adaptive factory water: a system dynamics approach. Environ. Model. Softw. 75, 348–361. http://dx.doi.org/10.1016/j.envsoft.2014.05.018.
Scheffer, M., 2009. Critical Transitions in Nature and Society. Princeton University Press, Princeton, NJ.
Scheffer, M., Bascompte, J., Brock, W.A., Brovkin, V., Carpenter, S.R., Dakos, V., Held, H., van Nes, E.H., Rietkerk, M., Sugihara, G., 2009. Early-warning signals for critical transitions. Nature 461 (7260), 53–59.
Scheffer, M., Carpenter, S., Foley, J.A., Folke, C., Walker, B., 2001. Catastrophic shifts in ecosystems. Nature 413 (6856), 591–596.
Scheffer, M., Carpenter, S.R., 2003. Catastrophic regime shifts in ecosystems: linking theory to observation. Trends Ecol. Evol. 18 (12), 648–656.
Smajgl, A., Bohensky, E., 2013. Behaviour and space in agent-based modelling: poverty patterns in East Kalimantan, Indonesia. Environ. Model. Softw. 45, 8–14.
Staver, A.C., Archibald, S., Levin, S., 2011. Tree cover in sub-Saharan Africa: rainfall and fire constrain forest and savanna as alternative stable states. Ecology 92 (5), 1063–1072.
Stern, N., 2008. The Economics of Climate Change: the Stern Review. Cambridge University Press, Cambridge.
Tavoni, A., Schluter, M., Levin, S., 2012. The survival of the conformist: social pressure and renewable resource management. J. Theor. Biol. 299, 152–161.
Vakhtina, E., Wosnitza, J.H., 2015. Capital market based warning indicators of bank runs. Phys. Stat. Mech. Appl. 417, 304–320.
Verstegen, J.A., Karssenberg, D., van der Hilst, F., Faaij, A.P.C., 2015. Detecting systemic change in a land use system by Bayesian data assimilation. Environ. Model. Softw. 75, 424–438. http://dx.doi.org/10.1016/j.envsoft.2015.02.013.
Vespignani, A., 2012. Modelling dynamical processes in complex socio-technical systems. Nat. Phys. 8 (1), 32–39.
Voinov, A., Shugart, H.H., 2013. 'Integronsters', integral and integrated modeling. Environ. Model. Softw. 39, 149–158.
Voinov, A.A., Tonkikh, A.P., 1987. Qualitative model of eutrophication in macrophyte lakes. Ecol. Model. 35 (3–4), 211–226.
Walker, B., Meyers, J.A., 2004. Thresholds in ecological and social-ecological systems: a developing database. Ecol. Soc. 9 (2).
Wiedermann, M., Donges, J.F., Heitzig, J., Lucht, W., Kurths, J., 2015. Macroscopic description of complex adaptive networks coevolving with dynamic node states. Phys. Rev. E 91 (5).
Winkler, R., 2005. Structural change with joint production of consumption and environmental pollution: a neo-Austrian approach. Struct. Change Econ. Dyn. 16 (1), 111–135.
Wissel, C., 1984. A universal law of the characteristic return time near thresholds. Oecologia 65 (1), 101–107.