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Regime shifts in coupled socio-environmental systems: Review of modelling challenges and approaches☆

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ABSTRACT

Increasing attention to regime shifts, critical transitions, non-marginal changes, and systemic shocks calls for the development of models that are able to reproduce or grow structural changes that occur over time periods perceived as abrupt. This paper highlights specific modelling challenges to consider when exploring coupled socio-environmental systems experiencing regime shifts. We explore these challenges in the context of four modelling approaches that have been applied to the study of regime shifts in coupled socio-environmental systems: statistical, system dynamics, equilibrium and agent-based modelling. When reviewing these modelling approaches we reflect on a set of criteria including the ability of an approach (1) to capture feedbacks between social and environmental system, (2) to represent the sources of regime shifts, (3) to incorporate complexity aspects, and (4) to deal with regime shift identification. Many of the modelling examples considered do not provide information on all these criteria, which receive a lot of attention in empirical studies of registered regime shifts. This suggests a need to develop a common modelling terminology in the domain of modelling for resilience and regime shifts. When discussing strengths and weaknesses of various modelling paradigms we conclude that a hybrid approach is likely to provide most insights into the processes and consequences of regime shifts. Challenges and frontier directions of research for designing models to study regime shifts in coupled socio-environmental systems are outlined.

1. Introduction

Large-scale natural disasters, destruction of vital ecosystem services, colonisation by invasive species, and socio-economic crises are currently at the top of the international agenda. Such events interrupt the functioning of economic, ecological, or coupled socio-environmental systems (SES), and may lead to a persistent change in system structure. Even in the absence of external disturbances, in the contemporary highly interconnected world, coupled SES are more vulnerable than they would otherwise be (Helbing, 2013).

In various disciplines, regime shifts, critical transitions, non-marginal changes, and systemic shocks are closely-related terms used to denote a structural change, often with a perceived sense of abruptness. Specifically, in the resilience literature a '*regime shift*' is a change from one system state to another, although this concept applies to cases where the transition occurs over any timescale, abrupt or otherwise (Walker and Meyers, 2004; Folke, 2006; Carpenter et al., 2011). The term is mainly used in ecology to describe significant, persistent changes in ecosystems – typically with vital consequences for socio-economic systems – which occur due to a switch in the dominant feedbacks that drive the system into a new regime (Biggs et al., 2009). The switch in the dominant feedbacks happens either as a results of a major external shock, or because the feedbacks dominating in the old regime are gradually eroding, passing a threshold after which new feedbacks prevail. As such, it is not unreasonable to apply the concept of regime shifts to socio-ecological or social systems (Schluter et al., 2012; Mueller et al., 2014; Lade et al 2013), despite the fact that the latter has its own vocabulary to describe analogous phenomena. Specifically, the socio-economic literature uses the term '*non-marginal change*', which is contrasted with gradual marginal change. Non-marginal change is a major change in the structure of

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Table 1
System states and drivers of change: a regime shift occurs in boxes III and IV; no regime shift in boxes I and II, due to system's resilience.

	Current regime is maintained	Regime shift
Disturbance	**I**. Recovery back to the same state	**III**. New state driven by exogenous disturbance
Gradual change	**II**. Remain in the same system state	**IV**. New state driven by endogenous or exogenous gradual change

an economy, shifting a socio-economic system onto a radically different trajectory, as opposed to its gradually moving along the same trend (Stern, 2008). Coupled SES are expected to experience major irreversible changes with non-marginal economic effects in a climate-changed world. Despite this, the majority of economic tools are designed to study exclusively marginal changes – i.e. small variations around a particular path. In economics '*structural change*' refers to a long-term fundamental shift in the functioning of markets and economic structure, moving them into a different state. Abrupt structural change is often linked to macro-economic cycles, such as Kondratieff waves, which under a Schumpeterian interpretation could feature 'creative destruction' during downturns, and are accompanied by observed shifts in the time series of socio-economic data (Medhurst and Henry, 2011). The term '*systemic shock*' is used in financial and environmental economics domain to refer to a major shift in a system state when normally uncorrelated markets and processes become correlated (OECD, 2003; Bhansali, 2008). Systemic shocks are global changes in the functioning of systems on which society depends. They may be driven either by micro-level gradual changes or external disturbances (e.g. natural hazards) (Filatova and Polhill, 2012). The resilience literature also uses the term '*critical transitions*', which are fundamental shifts experienced by systems when they pass bifurcations (Scheffer et al., 2012). A critical transition to a contrasting system state occurs when a system is approaching a catastrophic bifurcation – a tipping point – around which even small perturbations lead to a large change in system level variables. Positive feedbacks play a vital role in such transitions as they trigger a self-propagating shift to a different state (Scheffer, 2009). Thus, a critical transition is a special type of regime shift, which may occur without any major external shocking event (Andersen et al., 2009).

In this paper we use the term 'regime shift' as it is the most all-encompassing concept to describe the phenomena in which we are interested. A regime shift may be driven either by a disturbance or a gradual change (Table 1). '*Disturbance*' is an exogenous forcing in the form of a hazard event (e.g. hurricane, disease, fire) or in the form of an extreme change in an input variable (e.g. level of precipitation). After a disturbance, the system may either recover back to the same state (Table 1, I) or may shift to a new state[1] (Table 1, III), depending on the magnitude, rate of change, duration and frequency of the disturbance as well as the resilience of the system itself. (Gunderson and Holling, 2002; Folke, 2006; Scheffer, 2009). Turner and Dale (1998) review the differences between large infrequent and small frequent disturbances. According to Lake (2000) a disturbance may be in the form of a pulse (short-term and sharp), a press (a sharply-arising and maintained disturbance), or a ramp (a disturbance steadily increasing over time and space without an endpoint). Collins et al. (2011) simplify these ideas to two important kinds of disturbance: long-term sustained press disturbances and discrete, rapid short-term pulse disturbances.

A regime shift may also occur due to gradual changes in the system's components (Table 1, IV), which up to a critical point do not cause a shift in system state (Table 1, II). Regime shifts arising from gradual changes in explanatory variables (exogenous or endogenous drivers of response variables) have become especially apparent in a time of collapse of ecosystems, financial crises, housing bubbles, and climate change. In all these cases it is difficult to identify a single disturbance that caused a regime shift. Instead, it was gradual overfishing that led to the near-extinction of species and destruction of coral reefs (de Young et al., 2008); the slow accumulation of CO_2 and other green-house gases that caused climate change and its adverse consequences (IPCC, 2007; Stern, 2008); economic agents one-by-one adopting seemingly rational rules that caused structural changes in financial markets and economy (Anand et al., 2011); and the gradual spread of expectations among individuals of receiving a dividend from housing asset investments as housing prices grow annually driven by an increasing demand that was itself caused by those expectations (Arce and Lopez-Salido, 2011). Often a regime shift occurs when a system is moved towards a threshold by a combination of gradual changes and the shift is precipitated by a disturbance that would otherwise not be as harmful (Biggs et al., 2009).

Moreover, a regime shift may arise not only from gradual changes in a single variable, but from the interactions among processes operating at different spatial and temporal scales. As Carpenter and Turner (2000) point out, the time periods of changes in ecosystems span several orders of magnitude. A further complication is that the emergence of regime shifts from the bottom up in complex SES is embedded in heterogeneous spatial landscapes. The initial spatial correlation of site conditions and domino-effect responses across neighbouring cells strongly affect the consequent evolving patterns of a dynamic adaptive system (Scheffer, 2009). The effects of interactions among different processes across several variables are captured by concept of the 'perfect storm'. Here, the values of each of the variables taken individually might not be thought extraordinary, but collectively they form a highly unusual set of circumstances sufficient to cause a regime shift.

From a complex adaptive systems perspective, SES are seen as constantly changing, co-adapting, and perpetually out of equilibrium (Arthur et al., 1997; Folke, 2006). Marginal changes when a system gradually moves along a certain trend are quite "convenient" for decision-makers (and modellers), as prediction of future states can with a certain confidence rely on the historic trends and historic data. In other words, we know with a reasonable degree of certainty that with a unit change in driving variable(s) the response variable is likely to change in a predictable direction with a predictable extent. However, a growing body of literature suggests that it is common for complex SES to experience abrupt sudden shifts from one system state to another (Kinzig et al., 2006; Stern, 2008; Scheffer, 2009; Anand et al., 2011; Vespignani, 2012). A system experiencing a regime shift transforms into a system with new properties, structure, feedbacks, and underlying behaviour of components or agents. Macro variables of interest then do not change marginally with a gradual change in independent variables: there is a shift in the trend observed. These altered internal dynamics often prevent or impose a significant barrier to returning to the previous regime, and hence the possibility of regime shift occurring over relatively short timescales is of interest to decision-makers whose power and influence may be adversely affected. The

[1] A system *state* is not a steady-state or equilibrium, but rather a regime characterized by a certain system's structure, properties and functionalities (Folke, 2006).

number and diversity of regime shifts encouraged scholars to start collecting them to the Thresholds Database[2] and the Regime Shifts Database.[3]

As these critical events continue to happen, policy-makers need to find effective ways of managing the circumstances in which regime shifts occur (mitigation), or of reducing any negative consequences of regime shifts that cannot be avoided (adaptation). As Polasky et al. (2011) note, the probability of a regime shift could be exogenous (e.g. if management actions have no effect on the likelihood of a regime shift), or endogenous (e.g. when the probability of a regime shift is a function of a resource management policy choice). While empirical evidence based on historic data analysis is growing, anticipating an upcoming regime shift is still a challenge. The discovery of a range of early warning signals, which seem to precede many of the regime shifts registered in the past and which are universally observed in Earth sciences, medicine, and economics (Biggs et al., 2009; Scheffer et al., 2009), is a major breakthrough in this direction. Modelling tools to explore existing and potential future regime shifts and consequences under which they are likely to occur in coupled SES are therefore in high demand. Yet, the design of models to explore system resilience and occurrences of regime shifts is a challenging domain (Schlueter et al., 2012). The development of statistical, equilibrium and dynamic simulation models, which help our understanding of the emergence of regime shifts triggered by exogenous or gradual endogenous processes could support the design of resilient policies to manage SES. Studies of the dynamics of a system undergoing a regime shift tend to use a single modelling approach. However, a systematic overview of various modelling approaches to studying regime shifts is missing.

This paper provides an overview of how various modelling paradigms approach specific modelling challenges that are relevant for exploring coupled SES experiencing regime shifts. There are two main questions that guide this research. First, what are the important modelling aspects to consider when studying regime shifts? Second, how do various modelling traditions approach studying regime shifts? We focus on four main modelling approaches: statistical analysis, system dynamics, equilibrium models, and agent-based models, the motivation for so doing being chiefly driven by the fact that these are the four most commonly applied to the study of regime shifts in coupled SES.

The rest of the paper is organized as follows. First, based on a review of the resilience literature we identify four groups of modelling challenges that are essential to reflect on when designing and describing a model for exploring regime shifts (Section 2). Based on specific modelling examples, Section 3 describes the manner in which different modelling methods approach the study of regime shifts. These examples are reviewed using the four challenges (2.1–2.4) as evaluation criteria, with details summarized in Tables 4–7. Section 4 discusses how different modelling approaches address the four aspects, and reflects on their strengths and weaknesses when studying regime shifts. We conclude with a discussion of challenges to future modelling work and reflect on the use of modelling for the design of policies to mitigate or adapt to regime shifts.

2. Regime shifts and challenges to modelling

When reviewing the empirical regime shifts literature, we came across several themes that were discussed to varying levels of detail but consistently in almost every paper. In this section, we group these themes into four broad categories and discuss their implications for modelling in more detail. The categories are then used as points of reflection when reviewing the modelling approaches in the next sections:

1. *Feedbacks between social and environmental systems in coupled SES*. Links in models of coupled SES can be of three types: single linkages, a chain of one-way links or two-way feedbacks. Models representing more feedback loops may explain regime shifts that result from interactions or domino effects.
2. *Sources of regime shifts*. The new state can be driven by an exogenous disturbance or gradual changes originating in the natural or social system.
3. *Complexity aspects*. Models may describe different spatial or institutional scales and use varying approaches to thresholds and nonlinear effects.
4. *Regime shift identification* (detection, time-scales). Detection may focus on different system states, early warning signals or thresholds. Temporal scales of change vary from days to centuries. A change in internal dynamics may make a shift in a system state irreversible.

While these four categories appear in almost every empirical paper describing a regime shift, the modelling literature covers them neither explicitly nor consistently. Since the necessity of providing clear information on these four aspects arises from the practice of resilience research, we believe that doing so systematically in the modelling literature would help to integrate current modelling efforts in the accelerating domain of studying regime shifts in coupled SES. The implication of these four aspects for modelling is discussed in greater detail below. They also serve as criteria for reviewing the implementations of models for studying regime shifts across various modelling approaches in Section 3.

2.1. Feedbacks between social and environmental systems in coupled SES

A matter specific to coupled SES (and other multi-disciplinary) modelling exercises as opposed to single-disciplinary studies is that regime shifts may be triggered by the feedbacks between the socio-economic and ecological systems, not necessarily by the micro-macro feedbacks within one domain (Kinzig et al., 2006). Regime shifts may also be driven by a combination of anthropogenic and natural factors, when crossing a threshold in one domain causes cascading regime shifts across other domains. This highlights the importance of the modelling choice on how to represent these feedbacks when studying the resilience of coupled SES (Schlueter et al., 2012). Parker et al. (2008) distinguish between three types of model linkages to represent causality and feedbacks in SES. Namely, type 1 – one submodel serves as an input to the other (single linkages); type 2 – a chain of one-way linkages ('feedbacks' between two subsystems are represented as multiple acyclic linkages) such as environmental -> social -> environmental where the two environmental subsystem inputs and outputs may differ; and type 3 – feedback loop, in which there is full cyclic integration between environmental and social subsystems and shared variables between social and environmental subsystems are determined endogenously.

Table 2 summarizes the types of linkages between social and ecological systems in SES as described by Parker et al. (2008). We list the number of cases of registered regime shifts from the Threshold Databse[4] per type of link and indicate a subsystem in

[2] http://www.resalliance.org/index.php/database.
[3] http://www.regimeshifts.org.

[4] As at February 2013; the database is constantly updated.

Table 2
Linkages between social (S) and ecological (E) subsystems in SES: summary of cases of registered regime shifts.

A subsystem where a regime shift is registered	Type of links in SES	Number of studies
E	One-way S → E	31
E	One-way E → S	5
S	One-way E → S	1
E	E → S and S → E	20
S	E → S and S → E	4
S & E	E → S and S → E	10

Source: Thresholds Database, http://www.resalliance.org/index.php/database

which a regime shift occurs. Nearly all studies focus on regime shifts in ecosystems, with only 15 out of 71 cases dealing with regime shifts that manifest in social or socio-ecological systems. About half of the literature takes into account feedbacks between social and ecological systems, although the database does not always permit a distinction between a model composed of a chain of linkages and a fully-linked feedback-loop model.

2.2. Sources of regime shifts

As Scheffer et al. (2001) point out, a regime shift can be driven by external events (exogenous), or by internal dynamics that pushes the system across a threshold (endogenous). An exogenous disturbance to a model should appear in the time-series input data (and hence unaffected by the model's dynamics): examples include climate change scenarios and scenarios of crop prices or population growth/decline trends. Exogenously driven regime shifts can arise from a shocking event (pulse disturbance) or a gradual change (press disturbance). An endogenously driven regime shift is an emergent property of a system of interacting adaptive agents, processes and/or feedbacks across scales, and is largely fuelled by gradual processes.

The question of which variables are exogenous and which are modelled endogenously is determined by the boundary of a system. The choice of the boundary is subjective – made by a modeller (and sometimes determined by questions of tractability driven by the modelling approach) – but it can significantly affect the occurrence and detection of a regime shift.

2.3. Complexity aspects

2.3.1. Spatial and institutional scales

Coupled SES are characterized by multi-scale multi-domain feedbacks: the dynamics at various scales of an economic system affects the dynamics of a natural system at various spatial scales (Kinzig et al., 2006). While pursuing simplification, we may aggregate and average empirically observed data. This aggregation and averaging potentially omits micro-level dynamics, from which a regime shift could have endogenously emerged.

A choice of an appropriate scale is a challenge to SES modelling since there are mismatches between social and ecological scales (Cumming et al., 2006). A regime shift at one scale may not be pronounced or noticed at another scale. This is valid for scaling up in geographical spatial scales as well as in the number of agents in the system, when effects of heterogeneity and local interactions that are crucial for smaller-scale systems dissolve and disappear as the number of agents grows over several orders of magnitude – see for example (Gotts and Polhill, 2010). The implication for modelling regime shifts is that it may be necessary to test whether an exogenously- or endogenously-driven regime shift is observed (appears) when one scales up (down). A regime shift at a fine-grained scale may be hidden and its effects may not be pronounced on a coarser-grained scale of analysis. Hence, large-scale, often highly-aggregated models may omit the occurrence of a regime shift at lower scales, which are often more important for policy-makers if the implementation of policies is delegated to the local level. In this respect, the regime shifts database reveals that the vast majority of studies conducted so far (68/71) focus on the local or sub-continental scale instead of the continental or global scale.[5]

Social and environmental systems also often operate at different temporal scales. While socio-economic decisions in modelling practice may take place over an annual or quarterly timeframe, some ecological or climatic processes in natural systems undergo critical transitions in a timeframe of months, decades or centuries. Aligning temporal scales in coupled SES is thus a challenge in itself (Levin, 1992). If one aims at studying regime shifts in coupled SES this challenge is exacerbated by the fact that the choice of a temporal scale is crucial to its detection (see Section 2.4 for discussion).

2.3.2. Nonlinearities

Most coupled SES exhibit nonlinear behaviour (Liu et al., 2007). In complex adaptive systems it is often the case that many interacting agents follow nonlinear rules that produce complex dynamics at the macro level (Axelrod, 1997). In this paradigm, nonlinear effects and their macro-scale impacts stem from local processes, which shift from one state to another (Arthur, 1999). In its most extreme form, nonlinear behaviour is characterized by discontinuities (Liu et al., 2007). There are two main types of discontinuity (Huggett, 2005), which can be generalised to continuous cases using appropriately parameterised functions.

- Point discontinuities indicate the values of independent variables that cause sudden abrupt change in the dependent variable (Muradian, 2001). The gradient at the point in question is infinite (e.g. Heaviside function), or very large in the case of continuous generalisations (e.g. logistic-like function with a suitably large number in place of the base of natural logarithms).
- Zone discontinuities are intervals of the independent variables at which the change in the dependent variable is relatively rapid (Wiens et al., 2002). Here, the second derivative is infinite in magnitude at the start and end of the interval (e.g. ramp function), or very large in the case of continuous generalisations.

2.3.3. Thresholds

The term ‘threshold’ is used to describe the region in which there is a change from one regime to another (Muradian, 2001; Wiens et al., 2002; Walker and Meyers, 2004; Bennett et al., 2006; Kinzig et al., 2006). If they are known, then the crossing of thresholds can be detected and used as a surrogate for other measurements of the model's behaviour that indicate a regime shift. For instance, de Young et al. (2008) suggest that shifts in marine ecosystems can be predicted based on established causal relationships between coral reefs and fisheries or climate and a biogeographical shift.

However, the data for identifying thresholds are often absent or insufficient (Huggett, 2005). Moreover, there might be a time lag between the system crossing a threshold and the reflection thereof in the domain-specific macro-measures of interest that serve as indicators of the occurrence of a regime shift. Empirical research on marine ecosystems shows that while atmospheric changes and the resulting physical oceanographic responses detect a regime shift

[5] Source: Thresholds Database, http://www.resalliance.org/index.php/database.

quickly (in a year), the dynamics of various marine species in responses to these changes can take different spatial and temporal patterns (de Young et al., 2008).

Thresholds can also shift as a result of changes in other slowly changing variables, and crossing a threshold may be a necessary, but not a sufficient condition to indicate a regime shift (Kinzig et al., 2006). In addition, a regime shift may be caused by crossing thresholds defined over a multidimensional space (Huggett, 2005). So, even if a certain threshold is not crossed in one dimension, the crossing of thresholds in other dimensions may still lead to a regime shift.

Empirical research suggests that the positions of critical thresholds and chances of crossing them in one domain and scale react dynamically with the changes in other domains and scales (Kinzig et al., 2006). This phenomenon of a moving threshold is another issue to consider when designing a model that is able to capture regime shifts. When modelling thresholds that are explicitly specified, a perspicuous treatment of feedback loops in the model that adjust the values of the thresholds may be needed.

2.4. Regime shift identification

2.4.1. Detection

Representation of endogenously-generated regime shifts requires the representation of variables in which they are observed, and the processes and feedbacks that drive them. According to Kinzig et al. (2006) three to five key variables are able to capture critical changes in SES. For an exogenously-driven regime shift, a modeller has *a priori knowledge* of what the disturbance to a system is, and is interested in how this system responds. In the particular case where a model is designed to explore the conditions under which a *known* regime shift emerges endogenously, the problem should also be relatively trivial.

However, detecting an *unexpected* regime shift could pose more of a challenge. This requires a knowledge of the 'normal' bounds of behaviour of the system in at least two regimes: those the model is in before and after a regime shift has occurred. It is possible that knowledge of more regimes would be required if there are multiple possible regimes into which a model could shift as a result of a emergent regime shift. Moreover, a decision should be made on what degree of change in macro-measures of interest, which presumably characterize the structure and underlying behaviour of the elements of the system, constitutes a regime shift. A number of heuristics could be used to suggest that an endogenous regime shift has occurred: unusual values of macro variables, evidence of system restructuring, such as changes in connectivity of relationships among agents, or unusual model states that have not occurred in the real world.

Regime shifts may be detected either through time series analysis (see Section 3.1), or via detecting early warning signals of regime shifts, or by studying thresholds of explanatory variables (Table 3). While the detection of regime shifts in relatively simple systems is straightforward, such as the dominance of algae in coral reefs, it is a challenge for large-scale complex systems such as the world oceans (de Young et al., 2008). Regime shifts in oceans are not sudden and are asynchronous across ecosystem components; observing them requires comprehensive statistical techniques to analyse data gathered over decades to make sure the new regime persists. Integrating a socio-economic system with an environmental one in a single SES model does not simplify the process. Early warning signals are contested as indicators for regime shifts: they may merely show increased sensitivity of a system without necessarily predicting a regime shift (Kefi et al., 2013). Moreover, catastrophic collapse may occur without being preceded by early warning signals (Boerlijst et al., 2013).

Andersen et al. (2009) review quantitative approaches for detecting regime shifts focussing on ecological models and list available software for such detections. Rodionov (2005) lists an extensive number of statistical tests that can be used to detect regime shifts. Various methods can be used to detect shifts in the mean, variance, frequency structure or the whole system, yet they are highly data-intensive.

2.4.2. Temporal scales and reversibility

A potentially important element to a regime shift is its perceived 'suddenness'. Regime shifts that occur over several thousands of years affect no one individual significantly. A sudden regime shift is typically an event that takes place over a relatively short period of time in comparison with other processes. Even in the case of a regime shift arising from gradual endogenous changes within the system, the restructuring of the system can be an event that occurs over a relatively short timespan. For a disturbance, the same magnitude of change in a variable to which the disturbance is applied could, if applied over a longer time period, not cause a regime shift at all.

There is a possibility that an adjustment to a model events scheduling is required when simulating a regime shift, in particular for discrete-event models. Agents may need to make decisions over relatively short time scales than those they normally do, and may need to make different kinds of decision from those they take outside the context of an on-going regime shift. There may also be an issue with regime shift detection: it may not be recognized by looking from one time step to the next, but by comparing more temporally distant time steps.

Empirical cases of regime shifts feature a variety of temporal scale: from days and weeks (2 cases each out of 71 in the Thresholds Database[6]) to months (12), years (27), decades (13) and centuries (3). There is no guarantee of overlap between those of the environmental and socio-economic subsystems of coupled SES. An environmental process slowly changing over decades may be treated as constant in a shorter time scale of human decisions-making. This is closely related to the discussion of slow and fast variables, and myopia in socio-economic dynamics potentially leading to regime shift if the evolution of slow ecological variables is ignored (Carpenter and Turner, 2000). As reviewed by Carpenter and Turner, in ecology slow processes appear in the model as parameters while fast processes are endogenously determined as a model solution. However, since slow variables are also a subject to evolutionary change, these interactions between slow and fast time scales are essential for studying regime shifts.

A time scale of the duration of an old regime and the suddenness of the transition are important to judge upon the "persistence" of a new regime. After any regime shift there should be a period of time, however short, when the state of the model is not within the normal operating values of the regime it was in prior to its occurrence. In other words, the new state is irreversible or at least slowly-reversible. The persistence of a regime shift can be measured as the length of time it takes to restore the original regime. Reversibility is often viewed with respect to the ecological system – whether a previous, typically more 'natural', regime can be restored – rather than the social system. When the social system collapses, however, its restoration may simply be impossible, especially when the language, history and culture are lost. While reversibility is closely related to the magnitude of the disturbance and time scale of analysis, the fact that the time scale varies

[6] Source: Thresholds Database, http://www.resalliance.org/index.php/database.

Table 3
A variety of ways to detect a regime shift.

Means of detecting regime shift	Source
I. Identification of 2 distinct regimes	
- change-point analysis by sequential F tests	(Andersen et al., 2009)
- sequential t-tests	(Rodionov 2005)
- sequential STARS method	(Rodionov 2005)
- Regression based approach	(Rodionov 2005)
II. Identification of early warning signals	
- increased variability in time series data (raising variance, skewedness, kurtosis)	(Carpenter and Brock, 2006), (Biggs et al., 2009), (Guttal and Jayaprakash, 2008), (Scheffer et al., 2012)
- increasing autocorrelation (captured by slowing down of the fluctuations)	(Dakos et al., 2008), (Scheffer et al., 2012)
- increasing return time after disturbances	(van Nes and Scheffer, 2007), (Scheffer et al., 2012), (Kefi et al., 2013).
III. Identification of a threshold	
- principal component analysis (or empirical orthogonal functions, or singular spectrum analysis) for a better visualization of thresholds	(Andersen et al., 2009)
- chronological clustering (Ward's linkage method)	(Andersen et al., 2009)
- power spectral density	(Kleinen et al., 2003)
- Markov chain Monte Carlo	(Rodionov 2005)
- Lanzante method	(Rodionov 2005)
- crossing a known threshold	(Zhang et al., 2011)

significantly among case studies of SES experiencing regime shifts means it is impossible to make a general statement on time scales over which a regime shift could be considered irreversible.

3. Modelling approaches to study regime shifts

A variety of modelling approaches have been applied to studying the dynamics of coupled SES. These include analytical and statistical approaches, cellular automata, micro-simulation, computational general equilibrium, partial equilibrium, system dynamics and agent-based modelling. For the purposes of this review, we focused on those that present published examples with applications to study regime shifts in SES. We also tried to collect at least four examples per approach, pursuing the search for the appropriate papers in three stages. Firstly, we conducted an extended search using a variety of combinations of terms related to a regime shift phenomenon in different disciplines (including 'regime shift', 'critical transition', 'systemic shock', 'structural change', 'non-marginal change') and terms related to modelling (including 'model', 'statistical', 'system dynamics', 'agent-based', etc.). Secondly, we went through the Thresholds and the Regime Shifts Databases and traced individual authors and case studies to find related published work. Thirdly, we searched for models applied to study typical examples of regime shifts in one of the social or ecological domain (e.g. major disaster, eutrophication, collapse of civilizations, etc.), and selecting those with a link to the other of these two domains. In all three search stages we filtered the results to focus on models that were applied to study a regime shift in SES rather than social or ecological system alone. This three-stage search resulted in a collection of articles. While it provided examples of different models applied to studying regime shifts in SES, the papers varied significantly in the degree of detail when describing either the regime shift or the model.

The most common modelling approaches to study regime shifts are statistical, system dynamics, equilibrium, and agent-based models, all of which had at least four examples of models applied to regime shifts in coupled SES. We split equation-based models into two groups – system dynamics and equilibrium models – as they are designed with completely different theoretical paradigms in mind (focus on optimization in equilibrium models vs. focus on time as independent variable in system dynamics models). Thus, while the latter one studies results in terms of dynamics and alternative paths, the former concentrates on a comparison of two equilibria when discussing results. These four approaches are also interesting for their fundamental differences in character and emphasis that to some extent map onto the four thematic categories in Section 2. For example, statistical approaches are strongly aligned with detection; system dynamics model have a natural aptitude for representing feedback loops; equilibrium models are traditionally used to explore the impacts of disturbances; and agent-based modelling owes much of its origin to the complex systems literature (though this is not to ignore influences derived from an interest in exploring formalisations of social theories).

In what remains of Section 3 we present several examples of each of the methods, focussing on the essence of each modelling approach in the study of regime shifts. These examples are reviewed using the four challenges (2.1–2.4) as evaluation criteria, with details presented in the summary Tables 4–7 and discussed in Section 4.

3.1. Statistical models

Statistical models aim to detect or predict regime shifts through a statistical analysis of time-series of dependents and independent variables. Statistical analysis can help find patterns that allow extrapolation of the data. Yet, Andersen et al. (2009) notice that while appropriate statistical techniques existed for decades, their applications have been rare and limited primarily to ecological regime shifts. Rodionov (2005) and Andersen et al. (2009) provide an overview of statistical methods and software for detecting regime shifts. Those include sequential t-tests and F-tests for the differences in means and standard deviations in two (or more) regimes, chronological clustering, dynamical factor analysis, linear (e.g. Principal Components Analysis) and nonlinear dimensionality reduction methods, singular spectrum analysis, and so forth (see also Table 3). Contamin (2009) analyses a variety of regime shift indicators for prediction, which require statistical analysis. Biggs et al. (2009) and (Scheffer et al., 2012) highlight that statistical measures such as increasing variability, growing autocorrelation and slower recovery rates from disturbances serve as early warning signals of regime shifts. Several authors demonstrate the functioning of predictors, e.g. (Carpenter and Brock, 2006; Carpenter et al., 2011).

Statistical models may estimate a regime shift index, which is 'a cumulative sum of normalized deviations of the time-series values from the hypothetical mean level for the new regime' (Daskalov et al., 2007), Case 1 in Table 4. Alternatively, one splits time-series data into various segments, i.e. potentially various regimes, to run a statistical analysis (Table 3). Some statistical models allow

Table 4
Overview of statistical models examples per considered criteria.

Author and date	Phenomena considered	New regime representation	Feedbacks in SES (2.1)	Sources of regime shift (2.2)	Complexity aspects (2.3)			Regime shift identification (2.4)	
					Scales	Thresholds	Nonlinearities	Detection	Time scale
1. (Daskalov et al., 2007)	Overfishing and eutrophication leading to ecosystem regime shifts	Empirical	One-way linkage, shift in E due to pressure in S	Exogenous pressure amplified by endogenous dynamics (trophic cascade). Gradual	Single scale (Black Sea)	Single. Static, Estimated at various trophic levels.	Yes, ecological hysteresis nonlinear change across trophic levels	Automatic sequential algorithm to detect regime shift in time-series of species stocks with a cut off period of 15 and 7 years.	Decades (about 20 y) with partial recovery in 5–7 years. Full recovery is unlikely.
2. (Zhang et al., 2011)	Climate change and human crisis in 1500–1800 in Europe	Empirical	One-way linkage, shift in S due to forcing in E	Exogenous pressure exacerbated by endogenous socio-economic dynamics. Gradual.	Single scale (European part of Northern Hemisphere)	Single. Static, Estimated (real grain price of 0.2 is Granger-cause of humanitarian crises)	Yes, nonlinear response of population, famine, war etc. to temperature	Correlation and regression test; Granger Causality Analysis,; Multiple regression analysis.	Year-decade-century levels of analysis tracing the time-lags (5 y for food supply per person or 15 y for social disturbance).
3. (Krausmann et al., 2008)	Biophysical causes and consequences of industrialization in the UK and Austria	Empirical	Chain of one-way linkages, shift in E => shift in S => shift in E (other variable)	Endogenous, gradual.	Single scale (a country)	Single. Static. Observed (maximum population density)	Yes, stepwise process of decoupling energy production from land-use	Relationships between energy, land and labour. Flows and their directions.	Decades and centuries, irreversible
4. (Möllmann et al., 2009)	Regime shifts in the Baltic Sea due to atmospheric and anthropogenic pressure.	Empirical	One-way linkage, shift in E due to pressure in S	Exogenous amplified by endogenous (trophic cascade). Gradual.	Single (Central Baltic Sea)	Single. Static, Estimated (min of Regime Shift Index)	Discontinuities and ecological hysteresis.	Sequential regime shift detection method (STARS) applied on principal component analysis output. Cut-off length of STARS is 5 y.	Duration of a regime is 11–13 y, transition lasted 5 y.

automatic determination of the timing of regime shifts (Rodionov 2005) depending on the various cut-off lengths (i.e. the minimum length of a regime shift), which is a subject to a sensitivity analysis.

Statistical models can reveal not only correlations but also underlying causal mechanisms, e.g. using Granger Causality Analysis (Zhang et al., 2011), see Case 2 in Table 4, and thus improve the information available for the purposes of managing SES. An important restriction of statistical analysis is the availability of data. Contamin (2009) notes that ideally, statistical analysis is performed on multiple parameters that are easy to monitor and that are related to the processes causing regime shifts. Most statistical analyses of regime shifts in SES focuses on well-monitored aquatic systems and fisheries (Daskalov et al., 2007; Möllmann et al., 2009). There are also pure economic statistical models that study structural change in a system (Dahlquist and Gray, 2000).

The strength of the statistical approach in studying regime shifts is in its ability to identify abrupt as well as gradual regime shifts, without a need for information on the timing of those as it can be detected automatically (Möllmann et al., 2009). However, their applicability is contingent on the availability of large time series of data on both dependent and a range of independent variables.

3.2. System dynamics models

System dynamics (SD) models are characterisations of a system based on influences among variables over time using differential or difference equations. Influence is an asymmetric, transitive relationship, and feedback loops occur where a variable effectively influences itself through a path of influences that starts and ends with itself. Feedback loops can be reinforcing (the value of the variable continues on the trajectory implied by the sign of its first derivative with respect to time) or balancing (the value of the variable tends to an equilibrium).

Collie et al. (2004), in their review of modelling regime shifts in ecosystems using differential equations, distinguish three types of regime shift that can also be simulated with SD models because of strong links between the two approaches. First, smooth shifts pertain to linear relationships between the forcing and response variables. Second, abrupt shifts concern a sudden response of the response variables to a gradually increasing forcing variable. Third, a discontinuous regime shift entails an abrupt shift to another stable state due to the forcing variable passing a threshold. This shift exhibits hysteresis: when the forcing variable is decreased, the response variable will follow a different trajectory than before. The type of regime shift has implications for the characteristics of the SD models. The minimum number of possible equilibria varies as smooth shifts have one equilibrium, abrupt shifts have two equilibria and discontinuous shifts feature three or more equilibria, since hysteresis means there should be at least one alternative initial state (Collie et al., 2004).

SD models that study regime shifts typically include two-way feedbacks between social and ecological processes, and regime shifts are often caused by gradual changes in endogenous variables. Carpenter (2004) shows that SD models with multiple scales can account for decision making at different levels. SD models allow the identification of thresholds, stable states and unstable states (Table 5) through analysis of gradients.

There are two main strengths of SD models. First, causal loop diagrams can be elicited from participatory processes, and offer a purely narrative basis on which to describe and (qualitatively) analyse the system's responses to disturbances and shifts between regimes (Sendzimir et al., 2008, 2011; Tshimpanga, 2012), see Cases 2 and 4 in Table 5. Second, SD models of SES typically feature several feedback loops weaving between the social and ecological subsystems, see Cases 1–4 in Table 5.

Table 5
Overview of examples of system dynamics models per considered criteria.

Author and date	Phenomena considered	New regime representation	Feedbacks in SES (2.1)	Sources of regime shift (2.2)	Complexity aspects (2.3)			Regime shift identification (2.4)	
					Scales	Thresholds	Nonlinearities	Detection	Time scale
1. (Peterson et al., 2003)	Lake ecosystem management model. Regimes: eutrophic or oligotrophic lake.	Hypothetical scenario	Two-way feedback, shift in E due to pressure in S	Endogenous, gradual change	Single scale (lake ecosystem)	Multiple (parameter-specific). Static. Observed rather than estimated	Abrupt changes in utility and ecosystem functions response to gradual changes in belief and pollution.	Collapse of a lake ecosystem	Years
2. (Sendzimir et al., 2008)	Contrasting management regimes for the Tisza River Basin, Hungary	Hypothetical scenario (adaptive river management regime)	Two way feedback (numerous)	Endogenous change in management regime	Multiple (farms through to river basin)	Multiple. Dynamic. Estimated. Linked to barriers in switching between conventional and adaptive river management regime	Assumed in relationships among variables	Increased rate of flooding	Decades
3. (Pacheco et al., 2010)	Mayan collapse	Hypothetical scenarios	Two way feedback (population <-> agricultural productivity)	Endogenous gradual change with exogenous drivers	Single scale (national)	Multiple. Dynamics. Observed (switch between sustainable and unsustainable levels of population involved in non-agricultural activities	Several – e.g. relationship between per capita food availability and mortality rate; and between population maintaining terraces and agricultural productivity	"Death spirals" (reinforcing feedback loops that lead to ever-decreasing population).	Centuries
4. (Tshimpanga, 2012)	Smallholder livestock keeping and agriculture in sub-Saharan Africa	Empirical	Two way feedback (numerous)	Endogenous gradual change with exogenous drivers	Multiple (household through to landscape scale)	Multiple. Dynamic. Estimated (switch between sustainable and unsustainable agriculture)	Several – e.g. relationship between health and productivity	Poverty traps	Years

Formally (though some SD modellers stop at the qualitative stage), SD models are specified as systems of first-order differential equations, each of which captures the rate at which the level of one variable is affected by those of others. For this reason, SD modellers often characterise systems in terms of "levels and rates" or, equivalently (perhaps from its industrial origins (Forrester, 1961)) "stocks and flows". These equations are typically nonlinear, meaning that nonlinear thinking is embedded into the research paradigm. Once SD models have been specified formally, SD can be seen as a subset of ordinary differential equations models, which have the advantage of relative mathematical simplicity, potentially enabling tractable analyses of the range of potential system behaviour. However, they can struggle to elegantly represent heterogeneity among individuals in populations, where this is important. Veliov (2005) notes that ignoring heterogeneity may affect model outcomes significantly. For example, averaging critical variables rules out extinction scenarios in predator–prey models that do occur with ABM (Wilson et al., 1999).

This formalisation of SD models can be problematic where the original relationship was conceived qualitatively. There can be many ways to represent a relationship that is asymptotic in the response variable as the driving variable approaches plus/minus infinity, such as logistic or arc tangent (Dniestrzanski, 2008). Edmonds' (2005) reflections on the impact that a slight change in functional form has on an opinion dynamics model are relevant here, despite the fact that such models are (typically) agent-based. Specifically, Edmonds studied the model of Deffuant et al. (2002), which assumes that the influence of one person's opinion on another's is a decreasing function of the degree of difference (d) between the two opinions, but an increasing function of the uncertainty (u) with which the opinion of the subject of the influence is held. Edmonds found that changing the precise mathematical representation of this qualitative understanding from $\exp(-(d/u)^2)$ to $1/(1+(1.361\ d/u)^3)$ changed a simulation in which equilibrium opinions in the population were at two opposing extremes, to one in which the population eventually converged to a single, moderate opinion.[7] Indeed, the points made here are general to all modelling approaches involving the formalisation and numerical representation of qualitative concepts.

Further, stochastic events are not accounted for in deterministic SD models although they are commonly used in representations of decision-making. Indeed, Rahmandad (2008) notes that for instance hospital capacity cannot be decided on a single outcome but should be based on a distribution of outcomes. In such cases differential equation models can be complemented with a stochastic optimization model, as done by Ermoliev and Ermolieva, 2013. Heckbert (2010) also points out that while system dynamics approaches represent feedback and macro-level processes and complexity well, they have limited ability to evolve: only parameter changes can influence the structure.

3.3. Equilibrium models

Equilibrium models (EMs) study dynamic SES converging to equilibrium by finding a constraint optimization solution. The types of EMs applied to SES vary. In the partial-equilibrium modelling tradition, a typical formulation permits a model to endogenously select quantities of resource or service (including ecosystem services) exchanged. These models sometimes use differential equations. In contrast to SD models focussing on dynamics achieved

[7] Deffuant's (2006) response to this article found some further differences among numerical representations of opinion dynamics models, and sensitivity to network topology, but suggested robustness of results to the introduction of noise.

Table 6
Overview of equilibrium models examples per considered criteria.

Author and date	Phenomena considered	New regime representation	Feedbacks in SES (2.1)	Sources of regime shift (2.2)	Complexity aspects (2.3)			Regime shift identification (2.4)	
					Scales	Thresholds	Nonlinearities	Detection	Time scale
1. (Polasky et al., 2011), EM	Harvesting a renewable resource (e.g. fishery or global atmosphere). Regimes: catastrophic stock collapse or not.	Hypothetical scenario	Two-way feedback, shift in E due to an optimal management choice in S	Exogenous and endogenous regime shift scenario	Stylized model with no scale specification	Single. Dynamic (stochastic component of the natural system). Is a variable in the model, which potentially depend on a management choice	Abrupt changes in the stock of a renewable resource	Crossing a threshold. Changes in stocks or in system dynamics	Stylized model with no specification of time step. Presumably a year.
2. (Suzuki and Iwasa, 2009), EM	Socio-economic choice and lake pollution. Regimes: polluted vs. clean lake, (non) cooperation level	Hypothetical scenario	Two-way feedback, shift in S and E	Endogenous, gradual change.	Single scale (lake water system)	Multiple (parameter-specific). Static. Observed rather than estimated	Yes, social and ecological hysteresis	Pollution level and cooperation level	One shot equilibrium
3. (Lofgren and Robinson, 2002), EM (CGE)	Food trade. Regimes: food exporter or importer across 4 crops.	Hypothetical scenario	A weak one-way link to E via the spatial representation of S. Shift in S.	Exogenous, shocking event.	Multiple (households, regions, country)	Multiple (parameter-specific). Static. Observed rather than estimated	Discontinuous economy responses to exogenous changes	Shifts between importer–exporter status due to 80% −120% changes in prices	One shot equilibrium
4. (Eboli et al., 2010) EM (Dynamic CGE)	Climate change impacts on economic growth. Regimes: switch from gains to losses or vice versa	Empirical forecast	Chain of one-way linkages, shift in E => shift in S => shift in E (other variable)	Exogenous, shocking event amplified by endogenous processes.	Multiple (sector, region, world)	Multiple (parameter-specific). Static. Observed rather than estimated	Interactions of exogenous and endogenous processes result in a nonlinear path. Total effect on GDP is not just the sum of all individual sector effects	Changes in GDP per sector (in a magnitude of few %) from losses to gains or vice versa	A sequence of annual static equilibria from a period 2002–2100

through solving differential equations with time as independent variable, EMs focus on the comparative static analysis of equilibria, their properties and the conditions under which they occur as well as on optimal solutions. Cyclic feedbacks between subsystems of SES are realized through common variables, which are determined endogenously based on nonlinear dynamics within subsystems (Polasky et al., 2011; Suzuki and Iwasa, 2009), Cases 1and 2 in Table 6. The general-equilibrium literature encompasses economy-wide input–output models and computable general equilibrium (CGE) models. In CGEs several markets are represented in a single model. Such models could simulate exogenously-driven structural changes but hardly permit endogenous regime shifts (Lofgren and Robinson, 1999). CGEs are usually multi-region models; however, they rarely consider space explicitly. As an exception, Lofgren (2002) uses a spatial-network CGE to model endogenous regime shifts in international food markets, see Case 3 in Table 6. Dynamic stochastic CGEs are used to analyse aggregate economic processes through a sequence of intermediate equilibria.

EMs study regime shifts in a number of ways but generally with the same idea: comparing the status quo equilibrium and a state after a disturbance. This may take the form of a simple comparative static analysis (Roson, 2003). Alternatively, CGEs compare a reference-year equilibrium with an equilibrium estimated by "shocking" model parameters (Eboli et al., 2010), Case 4 in Table 6. As Wing (2011) describes it, at first, the social accounting matrix with socio-economic data is extended to enable pollution and resource depletion to be related to economic variables. A disturbance impulse is then given by defining a set of exogenous parameters. This makes CGEs useful for analyzing the impacts of exogenously-driven regime shifts only. Further, a pulse disturbance propagates through the system by solving a new equilibrium for several parameter values that represent exogenous shocks, such as macro economic shocks, new policies or disasters. Finally, the welfare impacts of a disturbance are estimated as the difference in aggregated welfare between pre-shock and after-shock equilibria. Dynamics CGEs follow the same process but thought a finer-state temporary equilibria (Eboli et al., 2010). In this case endogenous interactions between sectors may amplify the effect of exogenous regime shifts.

Among the strengths of CGE models are a 'solid microeconomic foundation', internal consistency and the flexible solution algorithms that allow for exceedingly disaggregated models (Borges, 1986). Furthermore, Borges (1986) mentions the possibility to derive better measures of welfare gains. For SES models, Wing (2011), Carbone and Smith (2008) and Espinosa and Smith (1995) point out that in deciding the utility of an equilibrium, the separability, complementarity and substitutability of environmental quality and other economic factors can be problematically decisive in the welfare impact of the pulse disturbance. A weakness of CGEs is the inability to show disequilibria or transitional dynamics (Böhringer and Löschel, 2006), which may be particularly important in modelling regime shifts. Roson (2003) uses a comparative-static model to study the impact of climate change but finds that a dynamic integrated model is more apt since climate change occurs progressively and human-natural systems interact dynamically. Such a model would however be 'overwhelmingly complex', thus posing a challenge to a field of research where regime shifts do matter.

3.4. Agent-based models

Hare and Deadman (2004) suggest that agent-based models (ABMs) provide a natural framework to represent coupled SES, and they are increasingly being used for this purpose (Altaweel et al., 2010; Polhill et al., 2011; An, 2012). The possibility of ABM to represent adaptive decision-making and interactions

Table 7
Overview of examples of agent-based models per considered criteria.

Author and date	Phenomena considered	New regime representation	Feedbacks in SES (2.1)	Sources of regime shift (2.2)	Complexity aspects (2.3)			Regime shift identification (2.4)	
					Scales	Thresholds	Nonlinearities	Detection	Time scale
1. (Axtell et al., 2002)	Population growth and collapse in ancient Anasazi civilisation	Empirical and scenarios	One-way linkage (environmental variability -> crop yield); Regime shift in social system	Endogenous, farmland productivity and degraded environment	Multiple scales (single household, historic Anasazi population)	Single. Static. Observed (no land to grow enough food)	Yes, through interactions between external (environmental) and internal (social) determinants of cultural dynamics	Regime shift entails rapid decline of population and complete abandonment of the Long House Valley, exodus	Centuries, reversible, total exodus
2. (Castella et al., 2005)	Land use dynamics in upland Vietnam	Empirical	One-way linkage (decisions of land managers -> land use change)	Exogenous (changes in land tenure)	Multiple scales (household and region)	Single. Dynamic. Observed (gap between agricultural production and needs)	Availability of land for rice production, population size (labour and food requirements) and growing of cash crops	Rapid decline in forest cover	Planned by authorities
3. (Evans and Kelley, 2008)	Deforestation and reforestation	Empirical	Two-way (since spatial externalities are included)	Endogenous	Multiple scales (household and township)	Multiple. Dynamic. Observed (linked to the availability of off-farm employment and population decline)	Yes, abrupt pulses of deforestation and regrowth in some scenarios	Switch between predomination of forestry and agriculture	Decades, reversible over centuries
4. (Heckbert et al., 2014)	Population growth and decline in ancient Maya civilisation	Hypothetical theoretical	Two-way	Endogenous	Multiple scales (household and national)	Multiple. Dynamics. Estimated and observed (various input and output variables)	Trade allows increase in population levels that creates the conditions for collapse	Qualitative descriptions of socio-ecological indicators (population levels, forests, soil quality, trade networks)	Decades, biophysically reversible, though not socially (Mayan civilisation collapsed)

make them suitable for complex systems featuring heterogeneity, feedbacks and adaptation (Heckbert et al., 2010; Le et al., 2012). An (2012) holds that learning may change human decision-making and needs to be understood in order to realize in-depth coupling of natural and human systems. Parker (2003) notes that ABMs of land use/cover-change provide several advantages over other models. The fine resolution and inclusion of heterogeneity and interdependencies mean that statistical information is better utilized and endogenous feedbacks can be studied. More importantly, since the models do not have to fulfil equilibrium criteria, they can feature discontinuous and nonlinear behaviour and cross thresholds between regimes. The emergence of a regime shift is often modelled by means of adaptive behaviour in response to environmental changes or socio-economic changes (Table 7). This is realized through individual or social learning, which can be implemented in a simple way (e.g. imitation) or more sophisticated machine learning algorithms may be used.

For all that they are acknowledged to be well-suited to representing SES, Filatova et al. (2013) point out that many ABMs of SES do not in fact represent full 'closed-loop' couplings of the environmental and social subsystems, drawing on Parker et al.'s (2008) classification of such couplings. Exceptions include Evans and Kelley (2008), Rouleau et al. (2009), Le et al. (2012) and Heckbert et al. (in press) which, to some extent, feature closed-loop couplings (see Cases 3 and 4 in Table 7). Le et al. (2012) is one of the most advanced ABM explorations of the effects of various feedbacks in SES, including the impacts of human learning and adaptation to the changes in the environment as compared to feedbacks under fixed behavioural patterns. Voinov and Shugart (2013) emphasise that coupling models and their accompanying software implementations is non-trivial, highlighting in particular the care that needs to be taken in creating a consistent, balanced underlying ontology, in order to avoid what they call 'integronsters': coupled systems with incompatible levels of detail, mismatches of spatial or temporal scale, or in the concepts represented by variables. These findings mirror those of other authors concerned about levels of coupling (Antle et al., 2004): namely that fully integrated models, rather than coupled submodels, are the preferred option (Frysinger, 2001) – a matter that has to be balanced with a preference for modularity in implementation (Leavesley et al., 2002). However, this is a point that all modelling approaches must guard against.

There has been an increasing trend towards more empiricism in ABMs of SES (Janssen and Ostrom, 2006; Filatova et al., 2013). Empiricism is one way to constrain settings for the large numbers of parameters that ABMs can have (Grimm and Schmolke, 2011), but there may be no data available for the analysis of regime shifts, or the regime shift to be explored may not have occurred previously in sufficiently analogous circumstances to permit the justifiable use of existing data in a different context. Large parameter sweeps summarising the dynamics of the system are thus less feasible than they are with the more stylised representations that are capable of showing attractors, bifurcations, equilibria, and the other paraphernalia of nonlinear analysis. Interestingly, Anand et al. (2011) complement the results of their ABM of stock market crashes with mean-field analysis made feasible with further assumptions made "for the sake of simplicity" (p. 6). However, whilst many authors take a similar approach, e.g. (Galan and Izquierdo, 2005), these are often with ABMs that are quite stylised in the first place, and authors in ABM have criticised simplifying assumptions in other disciplines (Johnson, 1998; Moss, 2002). A strength of ABM is its ability to explore 'life as it could be' (Langton, 1989), yet to achieve the same system coverage as the more formal analyses requires large-scale social simulation: multidimensional parameter sweeps across several scenarios of change, and accompanying large-scale data analysis techniques and visualisations. Until such tools are made easy to use for the social simulation community, ABMs applied to regime shifts tend more to compare one or two scenarios, e.g. Happe et al. (2008), or even use the comparison of scenarios to compare regimes, e.g. (Morrison and Addison, 2008; Rouleau et al., 2009), rather than providing an analysis covering the whole system state space.

4. Discussion

As Tables 4–7 show and Section 3 discusses, various modelling approaches are applied to the exploration of regime shifts. They give different levels of importance to the key modelling aspects that were identified in Section 2 based on the attention given to them in the empirical cases of registered regime shifts. It should be noted that the modelling approaches are at different stages of development. Perhaps because of this, they also differ in the number of instances of application to the study of regime shifts: statistical models have been used for decades to identify regime shifts while ABMs have a shorter history in this domain[8] with applications primarily in archaeology (Axtell et al., 2002; Janssen, 2009, 2010).

4.1. Feedbacks between social and environmental systems in coupled SES

While it is the interactions between the socio-economic and environmental systems, which can either amplify or weaken a regime shift in one of the subsystems, few models in Tables 4–7 implement full feedback loops. Most often it is a one-way linkage or at maximum a chain of one-way linkages between socio-economic and environmental systems. Yet, the presence of such incomplete or indirect linkages may potentially result in models with critical missing feedbacks (Parker et al., 2008). The EM approach to studying regime shifts provides examples of all three ways of realizing linkages and feedbacks. One-way linkages or a chain thereof prevail in statistical modelling. By contrast, feedbacks are a clear strength of SD models, which have them at the heart of their ontology. Whilst ABMs have the potential to model closed-loop feedbacks between the social and environmental systems, including exploration of the impact of feedbacks under adaptive versus fixed agent behaviour (Le et al., 2012), this is not yet standard practice.

4.2. Sources of regime shifts

Statistical methods focus mainly on a system response to an exogenous forcing, which could be exacerbated by endogenous processes (Table 4). These could be either due to a single event or achieved through gradual forcing. Data on the environment has been diligently collected over centuries, in contrast to socio-economic data, which is more difficult to trace back in time in a consistent manner. Data availability issues dictate that it is usually the shift in environmental systems on which statistical models focus. EMs provide examples of both exogenous and endogenous regime shifts, albeit that CGEs are exclusively applied to exogenous shifts. Some ABMs study regime shifts by contrasting results from runs with different parameter settings, one or more of which represents that the regime shift has occurred. However, other work in ABM represents regime shifts as driven by endogenous processes or exogenous time series. More challenging for ABMs is to achieve a sufficient coverage of parameter space to permit a study of the basins of attraction in the system. SD models tend to concentrate more on endogenous regime shifts; an endogenous perspective is integral to the approach.[9] This does not prevent SD models from using exogenous time series to stimulate regime shifts, but they are seen more as drivers of endogenous change.

4.3. Complexity aspects

General EMs of SES often consider a single scale of, for instance, a river basin or a lake, while CGE models run their analyses on multiple scales ranging from a representative household through regions and countries to the whole world. Statistical models analyse regime shifts primarily on a single scale. ABMs are able to address multiple scales, from micro to macro, and provided that heterogeneity at the individual level is not a significant issue, SD models can do so too.

Thresholds in EMs and statistical models are static and unique per variable in specified model settings. However, in EMs they are not estimated under scrutiny, as statistical models do, but are rather visually observed. Crossing thresholds may be represented using separate runs in ABMs, but in those that explore regime shifts endogenously, threshold crossing is observed in macro-level variables. SD models may also explore crossing thresholds through comparing runs with different model settings (as in Pacheco et al., 2010).

All modelling approaches implement some form of nonlinear behaviour. In EMs this is often achieved through discontinuous responses to exogenous changes or hysteresis. Dynamic CGEs also observe nonlinear alterations of a counterfactual path from the baseline equilibrium due to the interactions between endogenous dynamics across economic sectors and exogenous disturbance either amplifying or counteracting the latter. Statistical models report hysteresis as well as exponential rather than linear response of dependent variables to changes in independent ones. Nonlinearity is a key component of SD modelling, as this typically features in the functions representing the influence one variable has on another. Nonlinear model dynamics is a typical feature of ABMs driven primarily by micro-level behaviour evolution or social amplification of opinions and impacts of agents' strategies. As Izquierdo and Polhill (2006) point out, nonlinearity could also be implied in the use of if-then-else (and other flow control) statements in a program code affecting the behaviour of models. Such statements are common in representations of decision-making, particularly rule-based.

4.4. Regime shift identification

EMs are not particularly rich in representing time scales. Partial EMs often use a sequence of abstract time steps that are not necessarily related to the real time processes. In CGEs a regime shift occurs in one shot (e.g. reference year and the year of interest) or, as for example in dynamic CGEs, in a sequence of annual equilibria between the reference year and the year of interest. The detection of a new regime is primarily either an interpretation of a graph or just a qualitative judgement on the differences in the variables of interest that supposedly indicate a new regime. In such cases, no tests are done on EMS output to explore whether those differences have statistical significance, as for example statistical models would do. For the latter is it the core of the study to run several tests on, for

[8] Several projects, which aim to apply ABM to study resilience and consequences where regime shifts do occur, have started only recently: (1) ABMs exploring the impact of feedbacks in SES on resilience and SES capacity to cope with global environmental change http://erc.europa.eu/sites/default/files/content/pages/pdf/AAAS-FICHES_MSchlueter.pdf, (2) ABM studying climate-driven non-marginal changes in SES in hazard-prone areas http://www.utwente.nl/mb/cstm/news/VENI_grant_Tatiana/, (3) ABM exploring societal regime shifts in SES of mountain regions http://www.uns.ethz.ch/people/science/seidlro/Research.

[9] System Dynamics Society (2011) The field of system dynamics. http://www.systemdynamics.org/what_is_system_dynamics.html Accessed 26 June 2013.

example, changes in means and variances, to prove the differences in regimes. Statistical models analyse data over a range of decades or centuries with an annual time step. ABMs usually represent the effects of a regime shift through contrasting different macro measures under different parameter settings, including the ones that allow for growing a regime shift endogenously. While ABM output data could be quite rich ranging from agent-level variables to more aggregated measures to trace the emergence of some macro-phenomena, the possibilities of applying statistical tests for regime shift detection on ABM output data remain underexplored. Computational constraints and the availability of data as well as the interests of stakeholders in participatory ABM may both contribute to the tendency of ABM being used for shorter time-scales. Longer time-scales in particular will require either significant computational power, or more stylised, heuristic representations of decision-making. The qualitative study of regime shifts is possible with ABMs, as illustrated by Heckbert et al. (in press), and SD models also have a strength in this area, with the causal loop diagram providing a context in which to discuss the impact of regime shifts and how they may build up. Tshimpanga (2012) demonstrates how qualitative analysis of the causal loop diagram can be used to identify leverage points for intervention.

When modelling a regime shift, a new system state with new elements and their relationships has to be represented in the model. The capability to represent the restructured system entails the representation of processes that create and destroy agents and links among them, and allow decision-making processes to adapt. Thus, agent heterogeneity and learning are both potentially important aspects of a model. Modelling approaches that do not explicitly represent agents and the interactions among them need to demonstrate that the aggregate variables they use to capture these dynamics can somehow reflect the outcomes of the implicit underlying phenomena. Doing so convincingly may require data; however, there could be problems with obtaining data that represent the new system state. In particular, the data may not be generalizable to the modelled context or may be unavailable if the new regime does not have a precedent in the real world. Among the modelling examples reviewed 8 out 16 (Tables 4–7) employed data to represent a new system state of a known regime shift. However, none of the techniques considered addresses the challenge of representing a radical restructuring of the system explicitly with both entities and relationships between them changing as the system dynamics unfold.

Many articles presenting modelling examples with regime shifts do not always clearly describe the assumptions. Details of the four thematic categories in Section 2, which are considered important in the empirical literature on regime shift (see Sections 2.1–2.4), are often omitted. Given their prevalence in the empirical literature, we recommend that the practice of reporting these categories is adopted in the modelling literature. This would also encourage the presentation of new examples of models studying regime shifts in a coherent and transparent way.

While Tables 4–7 present details on how various models address the four thematic categories related to the study of regime shifts, the choice of the appropriate modelling approach also depends on some other pragmatic factors. Such factors include the research question at hand, data availability, whether the aim is to detect a known regime shift or one as yet not encountered, other goals and the context of the research, and access to computing power and data analysis methods, and the consequent need to simplify. Table 8 summarises[10] the strengths and weaknesses of the four modelling approaches to studying regime shifts. It covers the four thematic categories related to the concept of regime shift, which served as review criteria (with white background), and these additional pragmatic categories (with grey background).

In fact, there is no universal method that scores well on all issues. Often when choosing a single modelling approach one needs to make compromises. In the ideal case, the strengths of several modelling approaches should be united in a hybrid model. Carpenter and Brock (2004) apply a hybrid differential equation and discrete choice model to explore mutual dynamics of anglers' portfolio choices of fishing activities and locations to live, and fish population dynamics, which could experience collapses. Altaweel (2008) combines environmental SD model and social ABM to study the effectiveness of various crop management practices in the settlements in the first millennium BC northern Mesopotamia. Safarzynska (2013) proposes a design of a CGE model combined with evolutionary economics to analyse the aggregate effects of such regime shift as a major flood event. Regime shifts explored by these hybrid models benefit from the combinations of strengths of various tools, but also risk combining their weaknesses.

While the current study provides a systematic review of several examples of models studying regime shifts (Tables 4–7 and Section 3), it is limited to four most popular modelling methods only. A larger scale review of this sort is a potential subject for future work, especially when new examples of models exploring regime shifts in coupled SES – rather than only ecological or only socio-economic systems – appear in the literature. Such a review also awaits application of other modelling techniques as well as novel (or more frequently applied) combinations of the four reviewed approaches to the study of regime shifts, and might indeed be an exciting direction for future research in this field. A valuable contribution could also be made by the systematic application of alternative modelling approaches to studying the same regime shift and comparing the results. As far as we are aware this issue is on the modelling agenda of the current research effort in studying regime shifts and nonlinearities.[11] While this effort is very fresh with no published results yet, it has a great potential both in understanding the nature of modelling and emergence of regime shifts and in improving the reliability of the models.

5. Conclusions

One of the main aims when studying regime shifts in coupled SES is to understand their nature and thereby to find effective ways to manage circumstances in which regime shifts occur (mitigation), or reduce their negative consequences that cannot be avoided (adaptation). This, however, is an enormous challenge. Designed policies, particularly where they are accountable to an electorate, need to be simple to comprehend and communicate, and be perceived as fair. They thereby run the risk of omitting vital positive feedbacks in SES, promoting universal application of best-case practices when the best way of governing regime shifts is context-sensitive (Scheffer, 2009). Early engagement of stakeholders in the design and exploration of models applied to study potential regime shifts is essential for the acceptance of models' results, including exploration of policy options' impacts (Voinov and Bousquet, 2010). Moreover, while we tend to think of regime shifts as negative events (catastrophic regime shifts in ecosystems, a loss of equilibrium in economic systems), some are actually a part

[10] The categories in Table 8 are based on the modelling experience of the authors and our discussions with modelling peers on this topic, as well as from the reflections found in the reviewed papers.

[11] One example of such an effort is the recent EU project 'COMPLEX', which aims to compare the performance of various modelling types in studying abrupt nonlinear response in coupled SES in the next 3 years: http://www.complex.ac.uk/project/wp6/index.htm.

Table 8
Strengths and limitations of various modelling approaches for studying regime shifts. Notation: "√" means that a method can be used if a condition is satisfied, "–" denotes that it is impossible or difficult to apply a method when a condition is present, an empty cell implies neutrality.

Modelling context/conditions	Statistical	SD	EM (non-CGE)	EM (CGE)	ABM
Feedbacks					
one-way linkage	√			√	
chain of links				√	
feedback loops	–	√	√		√
Source of regime shift[a]:					
exogenous pulse disturbance			√	√	√
exogenous press disturbance	√	√	√		√
endogenous gradual change	√	√	√		√
Complexity					
multiple scales (spatial/institutional)	–		–	√	√
nonlinearity		√			√
thresholds	√	√			
Regime shift identification					
detection	√				
temporal scales & reversibility		√	–	–	√
Availability of data					
time-series of aggregated environmental data	√			√	
time-series of aggregated socio-economic data	√			√	–
disaggregated data					√
Treatment of a regime shift:					
test statistical difference between 2 regimes	√	–	–	–	–
reproduce a known regime	√	√	√	√	√
grow a potential regime shift	–	√	√	–	√
a simple comparison of scenarios	–			√	
Relation to stakeholders:					
stakeholders are (or could be) actively involved in modelling	–	√	√	–	√
state institutions issue contract research (macro analysis)	√			√	
Simplification vs. high computing demands:					
simplified assumptions	√	√	√	√	
access to computing power and data analysis methods	√				√
agents adaptive behaviour and learning	–			–	√
heterogeneity	–	–	–	–	√
out-of-equilibrium dynamics and path-dependence		√		–	√
explicit spatial representation		–	–	-	

[a] This largely depends on where one draws a system boundary. This choice determines which processes are represented endogenously, and is done either by a researcher, a team of experts or in the participatory settings.

of evolution and progress. What is universal for regime shifts with positive and negative consequences, however, is that models with which we study these processes should be able to accommodate this abrupt structural change and out-of equilibrium dynamics.

This paper provides an overview of four modelling approaches – statistical, system dynamics, equilibrium and agent-based modelling – that are applied to studying regime shifts in coupled SES. Examples of these modelling approaches were discussed according to a number of criteria including the ability of an approach (1) to capture feedbacks between social and environmental system, (2) to represent the sources of regime shifts, (3) to incorporate complexity aspects, and (4) to deal with regime shift identification. Many of the modelling examples considered do not provide full information on these aspects, which receive a lot of attention in the empirical cases of registered regime shifts. This suggests there is a need to develop a common modelling terminology in the domain of modelling for resilience and regime shifts. When discussing strengths and weaknesses of various modelling paradigms we conclude that a hybrid approach would provide the greatest insight into the processes and consequences of regime shifts.

This review of modelling regime shifts suggests a number of areas for future research:

- Explicit representation of feedback loops in the simulation models, which would allow tracing cascading effects when crossing a threshold in a subsystem or the SES may affect another threshold in the other subsystem, or emergence of the moving thresholds;
- Pursuing a proper statistical analysis of simulation models' output data using techniques for detecting regime shifts rather than presenting a simple comparison of scenarios with/without a regime shift;
- Addressing the data gap challenge, particularly in social systems, where quantitative data on interactions and social influence are conspicuously absent. Laboratory experiments, twitter data, use of various applications on mobile devices, massive online surveys or controlled online experiments – all are potential candidates for collecting data on behavioural rules of socio-economic actors and on potential behavioural change to be employed in modelling SES;
- Searching for suitable algorithms to represent decision-making in individuals and collectives without recourse to narrow assumptions of rationality and optimisation. Crises and bubbles in socio-economic systems come unexpectedly as models that assume rational decision-makers with perfect foresight into the future will rarely predict them. Imperfect information and bounded rationality lead to actions that may push SES through a critical threshold and cause a regime shift. Yet, there seem to be many ways to model bounded rationality. Insights from the behavioural sciences and artificial intelligence should be exploited more when developing models of decision-making in SES;
- Finding ways to represent radical regime shifts where, effectively, the model ontology (the classes of agent and/or object, their attributes and nature and structure of relationships and feedbacks among them) change.

Insofar as the recommendation of studying hybrid approaches constitutes something of a compromise, or risks the creation of inelegantly coupled models with clashes in the representation of scales, aggregations, states and processes, there is clearly a gap that could be filled by a revolution in methods for simulating regime shifts in SES that addresses the weaknesses of existing approaches. The challenge of representing radically novel system states in new regimes is a particular issue for all the approaches. However, there is also a role for modesty. Hofstede's (1992) use of the slogan "modesty in modelling" in the domain of decision support systems emphasised the need for model developers to recognise the expertise of end-users (p. 182) and adopt a pragmatic approach, avoiding the temptation to model everything in exhaustive detail (pp 53–54). In the context of modelling regime shifts in coupled SES, the slogan could be applied as a concept of radical uncertainty: models may be useful in computing the logical consequences of large sets of assumptions that are beyond the capacity of individual humans to reason with, but there are limits to the extent to which models can act as crystal balls for those wanting to control the future.

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