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Research

The potential of models and modeling for social-ecological systems research: the reference frame ModSES

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ABSTRACT. Dynamic models have long been a common tool to support management of ecological and economic systems and played a prominent role in the early days of resilience research. Model applications have largely focused on policy assessment, the development of optimal management strategies, or analysis of system stability. However, modeling can serve many other purposes such as understanding system responses that emerge from complex interactions of system components, supporting participatory processes, and analyzing consequences of human behavioral complexity. The diversity of purposes, types, and applications of models offers great potential for social-ecological systems (SESs) research, but has created much confusion because modeling approaches originate from different disciplines, are based on different assumptions, focus on different levels of analysis, and use different analytical methods. This diversity makes it difficult to identify which approach is most suitable for addressing a specific question. Here, our aims are: (1) to introduce the most common types of dynamic models used in SESs research and related fields, and (2) to align these models with SESs research aims to support the selection and communication of the most suitable approach for a given study. To this end, we organize modeling approaches into a reference scheme called "modelling for social-ecological systems research" (ModSES) along two dimensions: the degree of realism and the degree of knowledge integration. These two dimensions capture key challenges of SESs research related to the need to account for context dependence and the intertwined nature of SESs as systems of humans embedded in nature across multiple scales, as well as to acknowledge different problem framings, understandings, interests, and values. We highlight the need to be aware of the potentials, limitations, and conceptual backgrounds underlying the different approaches. Critical engagement with modeling for different aims of SESs research can contribute to developing integrative understanding and action toward enhanced resilience and sustainability.

Key Words: *adaptation; agent-based models; participatory modeling; structural realistic models; stylized or toy models; system dynamic models; transformation*

INTRODUCTION

Understanding the dynamics that arise from the interactions and feedbacks between people, societies, and the ecosystems on which they depend is one of today's major challenges (Carpenter et al. 2009). Social-ecological systems (SESs) research is an emerging field that focuses on the interdependence between humans and nature that underlies many sustainability problems. Resilience thinking is a perspective used in SESs research that emphasizes the interdependent, complex, adaptive nature of human-environment systems and their nonlinear behavior, uncertainty, and surprise (Berkes and Folke 1998, Norberg and Cumming 2008, Folke et al. 2016). It emphasizes the need to understand and manage change, both in terms of withstanding shocks and disturbances through persistence and adaptation and also using them as an opportunity to change major characteristics of the system fundamentally when ecological, economic, or social structures make the existing system untenable, i.e., to transform (Folke et al. 2010). Resilience thinking thus goes beyond earlier notions of resilience as the capacity of the system to withstand shocks, and beyond a single focus on resilience as a system property or outcome. When we refer to SESs research here, we refer to research that takes a resilience thinking perspective.

Modeling played an important role in the early development of the concept of resilience, particularly in shifting the view of ecosystems as systems that evolve toward a single equilibrium to systems with multiple stable states (Holling 1973). Models of multiple stable states in ecosystems, and regime shifts or transitions between them, are still widely used today (e.g., Biggs et al. 2009, Scheffer et al. 2009, Hughes et al. 2017). In the past, models have also been used in the practice of adaptive ecosystem management such as in the Everglades, USA, particularly to assess the range of possible outcomes of management measures in complex systems (DeAngelis et al. 1998, Gunderson and Light 2006). Recent research about SESs and their governance from a resilience perspective, however, involves very little modeling. This is somewhat surprising, given recent developments of modeling in related fields such as ecology (Grimm and Railsback 2005), land system science (Matthews et al. 2007), environmental assessment and management (Kelly et al. 2013), and social simulation (Halbe et al. 2015). These developments include the proliferation of novel approaches from complexity science such as agent-based modeling (Filatova et al. 2013) and novel forms of model application such as participatory modeling to support societal learning and policy processes (Voinov et al. 2016).

One reason for the limited attention to modeling in resilience-based SESs research may lie in the fragmentation of approaches across disciplines, which accompanies an often confusing diversity of purposes and model types, different underlying assumptions, problem foci, levels of analysis, and methodologies (Schlüter et al. 2012). Another reason may be an often rather narrow view of modeling among nonmodelers, based on experience with the use of simplistic economic models for policy

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support or complex biophysical models that follow a systems engineering tradition, both of which have limited applicability to the types of problems addressed by SESs research (Allison et al. 2018). Moreover, modeling adaptation and transformation of intertwined SESs is difficult and requires pushing modeling frontiers. Finally, the recognition of the context and path dependence of SES dynamics has resulted in a focus of resilience-based SESs research on in-depth case studies that allow for rich, context-based understanding of resilience management or transformation challenges (e.g., Olsson et al. 2008, Gelcich et al. 2010).

Broadening the use of models and modeling in SESs research may help address the challenges for analysis and governance resulting from the intertwined, diverse, and complex adaptive nature of SESs. Although the importance of social-ecological relations and interactions has long been recognized, there is still a lack of tools for analyses that go beyond the separation of social and ecological to account for social-ecological relations and feedbacks. SESs are dynamic systems that continuously change and coevolve. Capturing the dynamics that arise from complex interactions across multiple scales to influence adaptation or transformation is another challenge to which different modeling approaches may contribute significantly. These challenges pose interesting research frontiers for the field of SES modeling itself (Schlüter et al. 2012, Filatova et al. 2016, Schulze et al. 2017). Thus, we believe that a deeper engagement of the SESs research community with dynamic modeling, and of the modeling community with recent developments in SESs research, can help advance the field and enhance the understanding and governance of SESs as complex adaptive systems.

Here, our aim is to take a step toward that deeper engagement and encourage the use of modeling for the analysis and governance of SESs by introducing SESs researchers to the most common types of models and applications of dynamic modeling relevant for SESs research, and by providing guidance for identifying the modeling approach most suitable for the aims of a given study or activity. To this end, we propose the reference scheme "ModSES" (modeling for social-ecological systems research), which aligns different SESs research aims with suitable model types and applications along the dimension of increasing realism, from theoretical study to empirical case, and along the degree of integration of different disciplines, stakeholders, and knowledge systems, from mono- to inter- and transdisciplinary. These dimensions capture two key challenges in dealing with complex and wicked sustainability problems: the need to account for context dependence; and the need to study SESs as integrated wholes where humans are embedded in ecosystems, not as separate social and ecological systems, and to take into account different, often contested, problem framings, understandings, interests, and values when developing solutions (Tengö et al. 2014). Although ModSES is intended for modelers and nonmodelers alike, we have particularly developed it to support collaboration between field researchers and modelers because these collaborations provide exciting opportunities for addressing these challenges.

We first review past modeling studies in resilience research to highlight the early uses of modeling. We do not review the increasing numbers of SES modeling studies since 2012 because that is beyond the scope of this paper and has been done elsewhere (Schulze et al. 2017, Egli et al. 2019). Instead, we assess the use of different types of model and model applications in related fields that can support different types of overarching SESs research aims and challenges. The research aims and challenges reflect recent developments in resilience thinking, particularly the shift in focus from persistence toward adaptation and transformation, the importance of the intertwinedness of people and ecosystems, and the complex adaptive nature of these systems (Folke et al. 2016). We align these aims with different purposes of models and review commonly used model types in related fields that can serve the different purposes. The combination of a type of model, e.g., system dynamics or agent-based, with a degree of realism and degree of integration characterizes what we call a modeling approach. We align modeling approaches with SESs research aims within the reference scheme ModSES to guide their application for different SESs research activities. In our discussion of the potential of modeling for resilience thinking and SESs research, we highlight the need to move toward a broader use of models beyond scientific understanding to support communication and knowledge integration in inter- and transdisciplinary processes. We hope that ModSES will be a first step to help SESs researchers and people interested in using modeling to support adaptation and transformation processes to choose appropriate tools.

PAST USE OF MODELING IN RESILIENCE RESEARCH

Modeling played a seminal role in the early days of resilience studies in ecology and their extension to natural resource and ecosystem management (Holling 1973, Crépin 2007). Our review of 52 resilience modeling studies from 1998 to 2011 shows that most models were developed to understand and manage the persistence of ecological or natural resource systems to disturbance or change (Section 3, Table A1 in Appendix 1). The main aims of these studies were: to assess the persistence of a specific system, to identify persistence mechanisms, to develop methods and measures to analyze and quantify resilience, and to evaluate and develop management strategies. Models for management focused either on an exploration of impacts and trade-offs among different alternative management strategies or on finding optimal management strategies that maximize resilience and economic performance. Only four studies used modeling to understand and manage adaptation, and none addressed transformation. The latter has not changed much since 2012 (but see Zagaria et al. 2017).

The most common model purposes are understanding and decision or management support (Fig. A4a in Appendix 1). Models for understanding are mostly generic, equation-based models, whereas those for decision or managment comprise both generic models for the development of (optimal) management strategies or context-specific, often rule-based, models for assessing implications of alternative management strategies in particular case studies (Fig. A4b in Appendix 1). The prominence of generic models is in part a historical legacy of the origin of the first resilience models in theoretical ecology, or resource economics. Only approximately one-third of the studies use models that are specific to a case study. This situation limits their potential to address real world problems in which context-specific complex interactions determine system behavior. This low number may be an underestimate because case-specific models that have been used for the practice of adaptive (co-)management have rarely been reported in the scientific literature.

Many models focus on ecological resilience to an anthropogenic driver without accounting for feedback from ecosystem change to human behavior. The very rudimentary representation of the social system in many early resilience models strongly limits the possibility to address the implications for resilience of social-ecological feedbacks, for instance, the response of resource users to changes in ecosystem state. Where they have been addressed, e.g., in bioeconomic models that investigate optimal management strategies, they do so at a highly aggregate level such as the level of a social planner who has perfect foresight and they are generally prescriptive, i.e., they aim to determine optimal policies under extremely simplified assumptions, rather than trying to understand real-world dynamics. Feedbacks at the level of individual actors or organisms and feedbacks across levels or scales have largely not been addressed. The lack of inclusion of full feedback loops in SES models is still an issue in SES modeling today, as recently highlighted by Filatova et al. (2016) and Schulze et al. (2017). However, there are also promising developments of models that explicitly consider social-ecological feedbacks and resilience (Huber et al. 2013, Lade et al. 2013, 2015).

We provide more information on the selection of papers and their coding, as well as additional insights from the reviewed studies from 1998–2011, in Appendix 1. That information includes, e.g., the types of resources and social systems modeled, types of disturbances, inclusion of social-ecological feedbacks, and depth of model analysis.

MODEL PURPOSES AND ROLES IN SUPPORT OF DIFFERENT SOCIAL-ECOLOGICAL SYSTEM RESEARCH AIMS

Resilience thinking was introduced as a framework for the study and management of SESs that highlights the interplay between persistence and change across scales (Folke et al. 2010). Much empirical and conceptual research in recent years has focused on the capacity to transform toward more sustainable trajectories (e.g., Westley et al. 2013, Moore et al. 2014, Olsson et al. 2014). Increasing emphasis has been placed on the need to acknowledge the interdependence between people and the biosphere, and the complex adaptive nature of SESs (Folke et al. 2016). Resilience thinking, as a problem-oriented research field within sustainability science, has a strong emphasis on developing approaches and processes that support change in real-world, place-based, problem contexts. It also needs to build on disciplinary research and interdisciplinary frameworks to ensure conceptual soundness. Aims of SESs research thus span the whole range from generalization and theory building to on-the-ground support for transformative processes.

Along the tensions of addressing real-world problems and developing SESs theory through processes that integrate diverse knowledge systems and account for the complex and intertwined nature of SESs, we identify five overarching SESs research aims that may benefit from greater involvement of modeling: (1) to identify generic processes or principles that determine SES behavior, (2) to manage SESs as complex adaptive systems, (3) to understand the emergence of SES phenomena, (4) to generate transdisciplinary knowledge about social-ecological interactions and feedbacks, and (5) to support social learning and exploration of new pathways for societal transformation (Table 1). Aim 1 represents classical deductive ways of theory testing and building as practiced in economics or theoretical ecology applied to SESs research. Aim 2 addresses the challenges of managing complex adaptive SESs that are characterized by uncertainty, surprise, the potential for abrupt change, and unintended outcomes (Levin et al. 2013). Aim 3 relates to an increasing call for understanding SES outcomes as emerging from the microlevel actions and interactions of diverse human and nonhuman entities and processes by which they are constrained (Levin et al. 2013). This call includes identifying the complex causal processes that give rise to SESs outcomes such as resilience or adaptive governance (Biesbroek et al. 2017) and understanding the consequences for governance (as in aim 2). Aim 4 addresses the need to develop an integrative, transdisciplinary understanding and theories about social-ecological interactions and feedbacks to capture better the intertwined nature of SESs (Folke et al. 2016). Aim 5 represents work on SES governance and transformations, particularly research or activities that aim to support societal processes of transformation through action research, participatory processes, and other forms of stakeholder engagement.

These research aims have direct consequences for the purpose of the models used to address them. Models are always developed for a particular purpose (Kelly et al. 2013). This idea is important because the research or study aim and the associated research question (if applicable) determine the choice of the degree of realism a model should have, and thus, its complexity, as well as the degree to which it should build on scientific knowledge from one discipline, several, or a broader set of knowledge systems, including nonscientific ones. Both choices, about the degree of realism and the degree of integration, will influence the selection of system boundaries, the variables and processes that will be included in the model, how decisions will be made (based on theory, empirical data, or field observations), and how the model's validity will be evaluated. Common model purposes relevant for SESs research are system understanding, exploration, explanation, prediction, management support, communication, learning, and theory building (e.g., Kelly et al. 2013, Poile and Safayeni 2016).

Finally, models can play different roles within a research or participatory process, from serving as analytical, predictive, explanatory, or exploratory tools to providing a boundary object to bridge across the interface of theory and empirics (Baumgärtner et al. 2008) or science and society (Collier et al. 2011, Seidl 2015). Models can be prescriptive, aiming at identifying how SESs should be managed, or descriptive, aiming to describe, understand, and explain how SESs work. Classical roles of models are their use as tools for determining optimal management strategies or predicting the outcomes of management measures. Other roles that are increasingly common and possibly more useful in SESs research are serving as eye-openers, as arguments in disputed problem situations, or as objects to create consensus (van Daalen et al. 2002). The same model purpose can be associated with different model roles; for instance, the purpose of a model can be to capture key processes of a resource management situation in a particular place. This model can serve as a tool for predicting the consequences of a management measure or as an eye-opener about the side-effects of a particular management action. Several roles can overlap. However, it is important to make sure a model is adapted for the role for which it is intended, in the same way as it should be

Table 1. Social-ecological systems (SESs) research aims and corresponding model purposes and roles.

SES research aim	Example	Purpose of model	Role of model
Identify generic processes or principles that determine SES behavior	• Typologies or archetypes of SESs • Principles of resilience • Principles governing changes in SESs	• Understanding and theory building • Models aim to capture general system behavior and are often based on theory; generally not applied to specific systems, but to a class of systems	Analytical tool
Manage SESs as complex adaptive systems	• Development of optimal, robust, or adaptive management strategies that take uncertainty, different time scales, and nonlinear behavior of SESs into account	• Exploration, management support, prediction • Models aim to explore or predict system responses to policy or are used for development of optimal or robust policy	Tool for forecasting or prediction
Understand the emergence of SES phenomena	• Identification of micro-level social-ecological processes and mechanisms that give rise to macro-level SES outcomes • Understanding of interactions across scale	• Understanding and explanation • Purpose of model is to explore system behavior produced by complex interactions between actors and ecosystems; often based on empirical data; often developed for a specific case study	Tool for exploration and explanation
Generate transdisciplinary knowledge about social-ecological interactions and feedbacks	• Linking insights on human behavior with insights on nonlinear ecological dynamics to assess implications for natural resource management • Integrating insights on social and institutional change with insights on ecosystem dynamics to understand transformation	• Understanding, exploration, communication, learning, theory building • Purpose of model is to facilitate integration of disciplinary knowledge about ecological and social processes, test competing hypotheses, and experiment with a virtual system to enhance understanding and build transdisciplinary theory	Tool for exploration and experimentation; Boundary object for interdisciplinary knowledge integration
Support social learning and exploration of new pathways for societal transformation	• Development of shared understanding and solutions for a policy problem • Development of a vision for a sustainable future and strategies to get there	• Exploration, communication, learning • Purpose of model or model building process is to make explicit different system understandings of stakeholders, explore alternative development pathways, and support social learning	Tool for exploration or forecasting (scenario analysis); Boundary object, eye opener (van Daalen et al. 2002), myth buster (Smajgl and Ward 2015)

adapted to its purpose. An unreflected use of a model in a different role can be problematic.

To summarize, the aim of a given research project or activity determines the purpose of the model and its role in the scientific or participatory process. It also determines the degree of realism of the model, as well as the extent to which the model builds on inter-or transdisciplinary knowledge. We call the combination of a degree of realism of a model, the degree of integration of different knowledge in model design, and the type of model used, a "modelling approach". Next, we discuss different types of models commonly used in fields related to SESs research, and then explicate different degrees of realism that can be expressed with the different model types.

COMMONLY USED MODEL TYPES IN RELATED FIELDS

The numbers of model purposes and applications have increased with the development of new model types. The increase in computational power now allows for the design of complex, structurally realistic models. Different model types are more or less suitable for the different purposes and roles outlined above because they may lead to different choices regarding the trade-offs among generality, realism, and precision (Levins 1966). Different model types also allow for different types of analysis and represent top-down or bottom-up views of a system. For instance, generic, analytical models have a high level of generality at the expense of realism, can be analyzed using mathematical methods such as stability analysis, and represent a top-down view of the system in which individual system elements are represented as averages (Table 2). In contrast, structurally realistic models are often highly realistic at the expense of generality, are analyzed through simulations and statistical techniques, and represent bottom-up views of the system that incorporate heterogeneity of system elements. Different model types also have their origin in different disciplines, which influences the basic underlying assumptions about system dynamics (e.g., systems in equilibrium vs. constantly changing), model structure (e.g., from first principles vs. empirical data and understanding), human behavior (e.g., rational actor vs. rule-based decision making), and level of abstraction (e.g., stocks vs. individual entities).

We draw on model-based research and activities in the fields of ecology, resource economics, land system science, computational social sciences, and participatory natural resource management to identify different model types suitable for supporting the research aims outlined in Table 1 (Table 2). We also build on earlier reviews of model types and purposes in related fields such as land-use and land-cover change (Parker et al. 2003), integrated assessment (Kelly et al. 2013), regime shifts (Filatova et al. 2016), and transition research (Halbe et al. 2015). We complement these studies by including an analysis of the disciplinary origins and conceptual and analytical basis of different model types and purposes because they are critical for understanding assumptions

Table 2. Descriptions of model types.

Type of model	Origin or conceptual foundation	Formalization	Analysis	Examples of application	Literature examples
Dynamical systems models	Physics, theoretical ecology, economics	System of differential or difference equations representing rate of change of aggregate system variables	Symbolical or numerical analysis of fixed points, stability, attractors, bifurcations	Regime shifts, alternative stable states	Biggs et al. (2009), Scheffer et al. (2009), Figueiredo and Pereira (2011), Horan et al. (2011), Tavoni et al. (2012), Lade et al. (2017)
Bioeconomic models	Resource economics (Clark 1990)	Objective function representing control variable to be maximized given a dynamic resource and economic constraints	Control theory, optimization	Optimal management of resource with regime shifts, response of resource users to new policy	Smith and Wilen (2003), Crépin (2007), Dowling et al. (2012)
System dynamics models	Organization research (Sterman 2001), environmental studies (Forrester 1994)	Causal-loop diagrams, differential or difference equations representing rate of change of aggregate system variables	Time-based simulations, simulation games	Feedback analysis, identification of leverage points to change system dynamics	Carpenter and Gunderson (2001), Elsawah et al. (2017)
State-and-transition models, Markov chain models	Ecology (Westoby 1989), agricultural economics	Matrix of transition probabilities of states	Time-based simulations, analysis of emergent patterns and structural change	Resource use and regime shifts in rangelands or forests caused by natural or human drivers such as exploitation, fire, and climate change	Satake et al. (2008), Zimmermann et al. (2009), Bestelmeyer et al. (2017)
Structurally realistic models	Ecology (Grimm and Railsback 2005), social sciences (Epstein 2006), computer science	Computational representation of agents, their properties, and interactions with each other and their environment	Time-based simulations, analysis of emergent macro-level patterns, statistical analysis of simulation data	Emergent system-level patterns and dynamics, policy assessment taking spatial structure and agent diversity into account	Wiegand et al. (2003), Filatova et al. (2011), Grimm and Railsback (2012), Smajgl and Bohensky (2013)

that underlie each approach. Boundaries between model types are fuzzy, e.g., an agent-based model can also be formalized in difference equations, and model names can vary among disciplines. Major differences between model types are the level of aggregation (mathematical models often work with aggregate variables based on mean field approximation, whereas structural realistic models represent individual objects or agents and their interactions) and the methods used for solving the model (mathematical analysis vs. simulation over time).

Dynamical systems models, bioeconomic models, and system dynamics models are all based on dynamical systems theory, which is an area in mathematics that studies the behavior of complex dynamical systems. These models differ with respect to their construction, formalization, and analysis. Dynamical systems models are formalized as systems of differential equations that are analyzed to identify fixed points or steady states, assess their stability, and identify attractors, bifurcations, or tipping points. Models are often solved analytically, which strongly limits the numbers of variables and functions that can be included. Results are often presented graphically as state or phase-space diagrams. Dynamical systems models represent the system in a highly simplified and aggregate way, often building on well-known models from ecology such as the Lotka-Volterra predator-prey equations or from bioeconomics such as the Gordon-Schaeffer harvesting model (Gordon 1954). Their purpose is mostly to understand and predict general system behavior. Seminal work in ecology includes Holling's (1973) work on alternative stable states of ecosystems, as well as research on regime shifts, critical transitions, and early warning signals (e.g., Scheffer et al. 2009). Further fields of application include the dynamics of a natural resource under technological and demographic change (Anderies 2003).

Bioeconomic models apply economic theory to natural resources, most commonly, fisheries. They are analyzed to identify optimal management strategies by maximizing a production function that uses a natural resource and effort or labor as inputs. An optimization approach is used to find the effort that maximizes the profits of a single owner or a social manager under the constraints of the dynamics of the natural resource. Bioeconomic models are also used to simulate the development of an economic system of natural resource use over time (instead of optimizing a control variable). Simulation-based bioeconomic models are similar to system dynamics models (described next), with a specific focus on economic processes. Bioeconomic approaches are very common for policy assessments in fisheries, e.g., the effect of the introduction of a marine reserve on resource users and ecological outcomes (e.g., Sanchirico and Wilen 2001, Smith and Wilen 2003, Dowling et al. 2012). Most bioeconomic models in fisheries only consider economic drivers of resource users' decisions (van Putten et al. 2012). The same situation holds for the use of bioeconomic models in agriculture, although models assuming multicriteria approaches exist (reviewed by Janssen and van Ittersum 2007).

System dynamics models are often constructed using causal loop diagrams, which represent feedbacks that are assumed to drive the dynamics of a system. These models are often analyzed graphically by identifying the feedbacks that stabilize the system (negative or balancing feedbacks) and those that destabilize it (positive or reinforcing feedbacks), and assessing their relative strengths (see Marzloff et al. 2011 for a reef ecosystems example). Causal loop diagrams and the stocks and flows on which they are based can also be formalized in simulation models in which the change of the system at each time step is represented using difference equations. System dynamics models are analyzed by simulating them over time and studying the resulting system-level behavior (e.g., Baur and Binder 2015) or assessing the implications of management or policy interventions (Elsawah et al. 2017). The differences among dynamical systems models mainly lie in the approaches to analyzing the models, e.g., mathematical analysis of fixed points or equilibria vs. simulation of system development over time, which may or may not result in stable states (Elsawah et al. 2017).

State-and-transition models are used to investigate and communicate landscape changes over time (Bestelmeyer et al. 2017). They are based on the assumptions that the ecosystem under consideration can exhibit multiple alternative states and that transitions between states take place with a certain probability. The transitions are typically driven by the interaction of succession, disturbance, and management, and can lead to irreversible states (Daniel and Frid 2012). This type of model has been applied to a number of management-related questions involving forests, rangelands, and wetlands. State-and-transition models are strongly related to empirical data. Conceptual state-and-transition models that use boxes-and-arrows diagrams have also proven to be helpful tools to integrate local knowledge and to support the generation of hypotheses in participatory processes (e.g., Knapp et al. 2011, Kachergis et al. 2013 for rangeland management) or for qualitatively comparing different management actions (e.g., Bestelmeyer et al. 2004 for fire vs. grazing processes in a rangeland system).

Structurally realistic models represent a system as composed of entities (human and nonhuman), their interactions, and the environment in which they are embedded. They take structural aspects such as spatial arrangements, heterogeneity of actors, or their interactions through (social) networks relevant for a given research question into account, often at two or more levels. Structural aspects and decision making of agents are often formalized via rule-based approaches ("if-then rules") or decision trees, which allow a more realistic mapping of relevant processes than possible in generic mathematical models. In ecology, structurally realistic models are often called individual-based models; in social simulation and environmental research, models that include human actors are called agent-based models. They are a powerful model type to generate a mechanistic and multilevel understanding of SESs. Models representing different hypotheses about possible mechanisms can be constructed and model outcomes can be tested against empirical data (DeAngelis and Mooij 2005) using pattern-oriented modeling (Grimm et al. 2005). They are grounded in a complexity perspective and allow for an abductive approach to science in which model construction is inspired by well-grounded assumptions or theories, and model analysis follows an inductive approach in which data are provided by simulations (Griffin 2006). Their computational nature facilitates the construction of models that are more realistic than dynamical systems models or bioeconomic models and, thus, are easier to link to real world problems (Berger and Schreinemachers 2006, Janssen and Ostrom 2006, Smajgl and Bohensky 2013, Schulze et al. 2017) but are also more difficult to analyze. However, structurally realistic models do not aim to be as realistic as possible; they include details only where they are considered relevant to answer a given research question.

DEGREE OF REALISM OF A MODEL

Each model type can be used to develop a model with different degrees of realism, but some are more suitable for generic representations and others for high degrees of realism. For the purpose of our analysis, we distinguish between (1) generic or theoretical models whose structure and assumptions on causal relations are based on (bio)economic or ecological theory, (2) stylized or toy models that are built to represent only selected aspects of a system in a stylized way for the purpose of investigating their impact on outcomes, and (3) empirical models whose structure, assumptions, and parameter values are based on information and data from a specific case. In reality, of course, the boundaries of the three classes are fuzzy; an empirical model will often also include assumptions that are based on theory, and a theoretical model may be inspired by or tested in a particular case. Toy models are often built on a mix of theoretical and empirically informed assumptions. Because they have become quite popular, particularly with agent-based modeling, we briefly describe stylized or toy models in more detail.

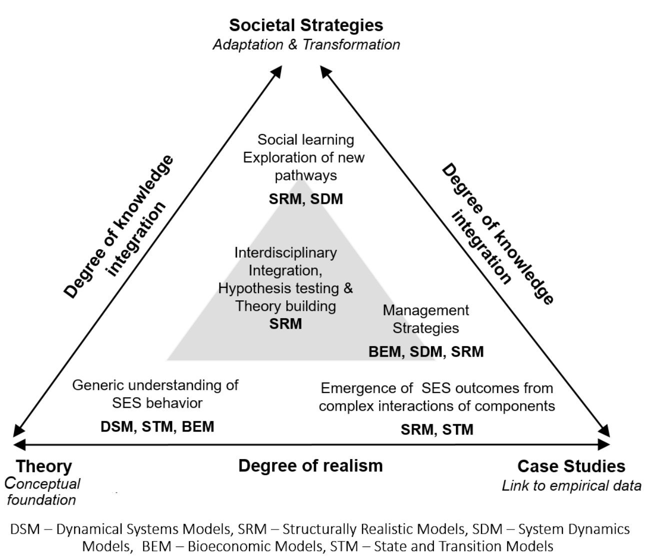
Stylized or toy models are "virtual laboratories" that facilitate computational experimentation with an SES in situations where policy experiments are not possible (Seppelt et al. 2009). They focus on a few, often hypothesized, aspects of a complex problem situation as a first step to enhance understanding of the behavior of a system. They are particularly useful in situations in which the quantitative knowledge base or the time frame available for model development is too limited for the development of structurally realistic models, or where a more complex model is too difficult and nontransparent to be well communicated to stakeholders. Their advantage lies in the possibility of exploring the consequences of different assumptions about social-ecological feedbacks and possible ecological and human responses. In such settings, toy models can serve as thought experiments for rapid development and testing of hypotheses to inform a field campaign (Turner 2003), to explore new strategies and development pathways, or to develop a model prototype to generate new hypotheses that can be tested later in more structurally rich models (Müller et al. 2011). For instance a toy model can be used to assess the potential and risks of new institutions, taking the response of the affected users into account. Management strategy evaluation, as applied to conservation, uses toy models to assess different types of uncertainties and their implications for wildlife management (Milner-Gulland 2011). Van Poorten et al. (2011) used a toy model of recreational fisheries to demonstrate how the panacea of stocking can emerge from management actions of bounded rational actors in a variable environment. These models can also serve as tools for communication and integration of different conceptual backgrounds and perspectives, as a basis for the development of management strategies (Daw et al. 2015).

The degree of realism needed for a given modeling study is a dimension well known to environmental modelers. Of particular interest here is the need to navigate the tension between the context dependence of social-ecological phenomena and the need to find generalizable insights to support management and governance.

LINKING RESEARCH AIMS WITH MODELING APPROACHES: THE REFERENCE SCHEME "ModSES"

The reference scheme ModSES delineates a space to map different research aims and align them with suitable modeling approaches. Each research aim and model type is mapped according to the degree of realism and degree of integration that models in support of this aim should incorporate (Fig. 1). The tensions between generality and realism and between science and society are struggles that different environmental modeling communities have faced for decades. Modeling studies aimed at addressing the former cover a range from theoretical to case-based research that differ with respect to the levels of abstraction and aggregation of relevant entities and interactions or processes (Baumgärtner et al. 2008). Studies addressing the latter are concerned with the complexities and context dependence of specific problem situations as well as the need to take into account different knowledge systems and coproduce knowledge with stakeholders (Tengö et al. 2014). The nature of these tensions is the same for SESs research, but with some important nuances related to the complexity and intertwined nature of SESs, where humans and ecosystems coconstitute and affect each other across all scales (Folke et al. 2016). This situation requires a focus on social-ecological relations and interactions as the core processes determining outcomes, which significantly goes beyond an ecological model that incorporates human action as a driver, or an economic model that regards ecosystems as an input to a production function (Schlüter et al. 2012). This focus on interdependence poses additional challenges for the degree of integration and the degree of realism because social-ecological relations can play out differently in different contexts.

Fig. 1. The reference frame "modeling for social-ecological systems research" (ModSES). The gray area indicates the location of stylized or toy models, which can be built using different model types. SES = social-ecological system.



Erratum: In the original publication of Figure 1 a label on the x axis was missing. The omission was corrected on 8 May 2019.

Our alignment of research aims with model types, degrees of integration, and realism is based on an assessment of the characteristics of different model types and a review of their use in other disciplines. Additionally, it is informed by many years of the authors' modeling experience in ecology, environmental systems, natural resource management, SESs, and participatory processes using all types of models highlighted here. When assessing the suitability of a model type for a research aim, the following two criteria are of importance. First, the research aim and research question determine the level of aggregation of the elements in the model (e.g., subsystem, aggregate variable, or individual agent) and level of realism needed in a model. Different types of models allow different levels of aggregation and realism; for example, a dynamical systems model cannot incorporate individual characteristics of actors or organisms and is very restricted with respect to its complexity because of the mathematical analyses used to identify fixed points and their stability. In contrast, a structurally realistic model disaggregates a SES into agents (individual or collective actors such as farmers or households or tree functional groups) and their interactions with each other and their environment. That type of model can be implemented with a high degree of realism as an empirical model that is parameterized with empirical data or as a toy model that is based on hypotheses about agent interactions that may be informed by empirical observations or theory. These models, however, can only be analyzed through statistical analysis of the outcomes of time-based simulations.

Second, some types of model have been used more commonly for specific research aims than others. For example, dynamical systems models have rarely been used for participatory modeling, whereas structurally realistic models are rarely used for theory testing. Finally, models can be predictive or explorative, and descriptive or prescriptive, which influences the choice of model type for a study or application. If the purpose of a model is to identify an optimal management strategy for a fishery, a prescriptive bioeconomic model solved to maximize a utility function will be most suitable. If the purpose is to understand how the diversity of human behavior affects the outcomes of a fishery, the choice will be a descriptive structural realistic model that enables representation of heterogeneous fishers and their interactions with fish stocks.

At the lower left corner of ModSES (Fig. 1) lies the aim to identify generic processes or principles that determine SES behavior, which is often supported by dynamical systems models, bioeconomic models, or theoretical state-and-transition models, which generally rely on theory and methods from the respective disciplines, particularly ecology and economics. This modeling use has been one of the most common in early resilience research, building on Holling's (1973) seminal work on the stability of ecosystems, and a large body of research on critical transitions (Scheffer et al. 2001, 2009, Brock and Carpenter 2006). These models are predominantly developed and used by scientists.

At the other end of the horizontal axis in the lower right corner (Fig. 1), one can find structurally realistic models or state-and-transition models, which are based on knowledge and data from a particular place such as a landscape (Spies et al. 2017) or a fishery (Libre et al. 2015). Structurally realistic models or state-and-transition models have a high degree of realism, with the aim of understanding the emergence of SES outcomes from local interactions or from changes in state of its components, respectively. These models are often used to explore the effect of policies (e.g., Daloğlu et al. 2014 for agriculture, Bino et al. 2015 for floodplain management, Thulke et al. 2018 for animal diseases) or the future development of the SES under climate change or other external disturbances (Millington et al. 2008 for wildfire). These models often capture structural details of a particular setting such as spatial patterns or social or ecological networks in a bottom-up manner using empirical data from the case study. Structurally realistic models such as agent-based models are particularly suitable to capture spatial aspects of the studied SES (Filatova et al. 2013). The development of these detailed case-based models is carried out by scientists, often from a specific discipline such as landscape ecology, but can include data collected through stakeholder interviews, surveys, or focus group discussions.

When moving along the vertical axis toward the middle-right of the ModSES triangle (Fig. 1), modeling purposes change from a primary focus on understanding to a focus on policy, management, and decision support. In addition, the degree of inclusion in model development or analysis increases for different domain experts and stakeholders. The use of models to support management is one of the most common uses of modeling in environmental research and is increasingly used in SESs research (e.g., Chapin et al. 2003, Schouten et al. 2013). Models for management are often developed for a specific case study but their degree of realism can vary greatly. Bioeconomic models apply economic theory to particular cases to determine optimal management strategies (Anderies et al. 2002, Crépin 2007); in contrast, structurally realistic models test the consequences of different management strategies, taking the complex adaptive nature of SESs into account (e.g., Little et al. 2009, Walsh and Mena 2016). System dynamics models are also a common model type that can include more realism than bioeconomic models but still model the system at an aggregate level in which system dynamics are represented as stocks and flows. In these modeling approaches, stakeholders are sometimes involved as experts to inform model structure, identify management priorities, or prioritize management measures and rank outcomes (e.g., Reichert et al. 2013).

In the middle-left of the ModSES triangle (Fig. 1), we find research aims related to the development of inter- or transdisciplinary understanding and theory of SESs. Models and the modeling processes can be useful tools to support social-ecological integration in inter- or transdisciplinary processes (Nicolson et al. 2002, Lade et al. 2015). Structurally realistic models that have a degree of realism characterized as stylized or toy models are common tools for this research aim (gray area in Fig. 1). Their realistic but selective representation of real systems makes them simple enough to be developed quickly and to serve as a tool for exploring different hypotheses about causal relationships. They thus allow for rapid prototyping and experimentation within an iterative process of model development and empirical research. They can support interdisciplinary knowledge integration through a process of codevelopment of the model by representatives of different disciplines. This process requires participants to define the concepts they use and make explicit their understanding and assumptions about the SES (Nicolson et al. 2002, Olson et al. 2008), thus facilitating integration of knowledge on ecological and social factors and dynamics of the studied SES phenomena (e.g., Lade et al. 2015). However, given their simplistic nature, toy models are often difficult to validate and thus should be used in a larger context of field and experimental studies or an adaptive management process.

Lastly, the use or codevelopment of models in participatory processes (participatory modeling) has become a widely used method in environmental assessment and natural resource management (Voinov et al. 2016), with the aim of supporting social learning and the exploration of alternative development pathways through scenario analysis (e.g., Carpenter et al. 2015). Models in participatory processes can serve as boundary objects (Mollinga 2010) that help reveal differences in problem framing, values, and goals, and can help to enhance transparency, build trust, and facilitate communication on complex SES relationships (Campo et al. 2010). However, the process and context of the development and use of models in participatory processes, as well as their integration into the larger decision-making process, are critically important for their success (Lynam et al. 2007). There are a range of goals for participatory modeling: (1) using a participatory process to increase the real-world impact to modeling; (2) enhancing system understanding and problem perceptions of participants, e.g., to recognize trade-offs and potential conflicts and develop strategies to resolve them, thus enhancing problem-solving capacity (Sandker et al. 2010, Dumrongrojwatthana and Trébuil 2011); (3) facilitating exploration of likely social-ecological consequences of decisions, (4) supporting communication and learning among participants; (5) coproducing a model to achieve a problem definition that is relevant to the diversity of stakeholder values in a system; and (6) supporting conflict resolution (Lynam et al. 2007, Prell et al. 2007, Voinov and Gaddis 2008, Smajgl 2010). A range of different model types are used, with agent-based or system dynamics models being most prominent. Models can either be brought into the participatory process by scientists or be codeveloped with stakeholders to represent their system understanding and problem perception (also called mediated modeling or companion modeling; van den Belt 2004, Etienne 2012). Often, they are combined with role-playing games, a combination that has been shown to facilitate problem solving and relational learning in complex problem situations such as river basin management (Gurung et al. 2006, Stefanska et al. 2011).

DISCUSSION

ModSES is intended as a tool to help modelers, nonmodelers, students, policy makers, and other stakeholders interested in using models or modeling for SESs research to navigate the diversity of model types as well as model building and application processes used in SESs research and related fields. It can be used to create awareness of the different modeling purposes and help guide or justify the selection of a particular model type. It also facilitates communicating a chosen approach and application to other researchers and stakeholders by situating it along two dimensions: generality–realism and science–society. The two axes of ModSES merge at the top, indicating that approaches supporting societal processes of adaptation and transformation need to incorporate sufficient realism and be of a transdisciplinary nature. For instance, strategy development and social learning can greatly benefit from the use of place-based modeling approaches that aim to unravel causal mechanisms operating in a specific context. There is also a need to generalize from individual cases in a way that does justice to the importance of context, i.e., by developing contextualized generalizations. Such an understanding of key mechanisms at play in different contexts can provide valuable insights about entry points for governance. Ultimately, there will and should always be studies situated at different locations along these two dimensions, depending on the purpose of the model or the larger study in which it is embedded. A study may also include several different model types to address different aspects of the SES or stakeholder needs and to benefit from different insights into the problem they may provide. The usefulness of modeling studies can, however, be significantly enhanced when the choices of degree of realism and degree of integration are well documented and justified, and when researchers are aware of the possibilities and limitations of each approach.

ModSES is intended to be neither comprehensive nor exclusive with respect to the types of models included or how to map them onto the different research aims. Other combinations are possible and likely, e.g., a dynamical systems model with low degree of realism but high degree of integration used for social learning; however, they are less common and sometimes may be incompatible because of conflicts in underlying assumptions. Other modelers may disagree with some of our choices based on different experiences and interpretations with regard to which models are most appropriate for which research aim. Nevertheless, we believe that the scheme is useful for providing an orientation and guide about different possibilities of modeling in support of SESs research, particularly for those interested in developing their first model or collaborating with modelers. We have encountered much confusion with respect to what a model is and can or cannot do. We hope that ModSES will provide some clarity and a tool through which modelers can explain their models and how and for what purposes they can be applied.

The choice of a modeling approach is also a choice of a conceptualization of the system of interest that will influence the types of possible outcomes and the suitability of the approach for a given task. The different model types have their origin in different disciplines or research areas, which have different ontologies, epistemologies, and methodologies. An understanding of the conceptual foundations and system understanding associated with a type of model is thus essential for a sensitive use of the different approaches. Models that are based on dynamical systems theory such as bioeconomic models, for instance, are generally based on a view that the heterogeneity of system components can adequately be represented by averages or representative individuals such as a representative agent. Models that are based in complexity theory such as agent-based models are based on the view that heterogeneity and local adaptation are important for system-level outcomes and that human decision making is boundedly rational or follows other decision-making models.

The choice of the level of aggregation for a model, whether elements can be represented as aggregate stocks or as individual entities, matters whenever spatial structure or heterogeneity of entities may influence outcomes. Railsback and Harvey (2011) used a structurally realistic model to show that common theories of food limitation for animal populations do not hold when individual behavior of organisms is taken into account. Their model of fish populations that included habitat complexity and fish physiology revealed that active behavior of fish causes positive feedbacks that sustain food limitation despite an increase in food availability. This result can have important implications for conservation strategies. Structurally realistic models have also proven useful to reveal the effect of social heterogeneity on the dynamics of SESs, for example, the effect of agents' heterogeneity on the outcome of policy interventions (Smajgl and Bohensky 2013).

Models are simplified representations of reality in which the process of simplification is guided by the knowledge and assumptions of those involved in the model development process. Model results should always be interpreted in light of these assumptions and the underlying system conceptualization. The documentation of assumptions and choices made when implementing an approach and a discussion of limitations are thus of utmost importance. Recently, several tools have been developed to support more transparency on modeling choices (Grimm et al. 2006, Müller et al. 2013, Schlüter et al. 2014). Model assumptions are also critical for the applicability of a model for policy support. For instance, the choices about how to model human behavior have implications for the design of policies because the response of resource users to policy determines its effectiveness (Fulton et al. 2011). Models are increasingly being used to test consequences for SES outcomes of alternative assumptions about human behavior (Janssen 2016, Beckage et al. 2018) or social-ecological relations (Lade et al. 2017) to understand better the uncertainty associated with the complexity of human behavior and biophysical processes.

Many challenges remain to realizing the full potential of modeling for analysis and governance of SESs. Our review of past resilience modeling studies shows that many models lack links to the real world, which reflects the difficulty of building empirically based models of truly interdependent SESs, particularly with regard to integrating social science with natural science concepts and data and accounting for different levels of analysis (Janssen and Ostrom 2006, Smajgl and Barreteau 2014). Combinations of different model types in hybrid models, e.g., dynamical systems models with agent-based models, are a way forward to address different levels of aggregation and make use of the strengths of several approaches (Martin and Schlüter 2015). New modeling approaches have also recently been developed that are promising for the development of integrative empirical models of regime shifts using generalized modeling (Lade et al. 2015, Lade and Niiranen 2017) or the dynamics of social networks (Wiedermann et al. 2015). However, there remains a dilemma for policy support because models that are aimed to predict or optimize often do not account for complex social-ecological interactions, whereas those that capture social-ecological interdependence are normally not intended for prediction (Allison et al. 2018).

Two major challenges of SESs research in which a broadened use of modeling may be particularly interesting are the development of generalizable insights that do justice to the context dependence of social-ecological processes, and the development of understanding and theory of SESs that is truly integrative and builds on bridging between disciplines and knowledge systems to capture social-ecological interactions and feedbacks across scales and develop strategies for transformation. The lack of models of transformation itself (not modeling to support transformation) may reflect the difficulty of modeling systemic reorganization (Polhill et al. 2016). This is an interesting research frontier for SES modeling, particularly with respect to how models can help identify social-ecological mechanisms of transformation in complex and continuously changing SESs and generalize beyond single case studies. One of the largest benefits of models in SES research, however, may actually be their potential as process tools whereby they serve as boundary objects to challenge thinking in disciplinary silos, and explicate differences in values, worldviews, and understanding between different knowledge systems, and thus, help to move toward more integrated understanding and the development of widely accepted and co-owned solutions. Particularly, simple inter- and transdisciplinary toy models may be of use to address wicked problems for which traditional disciplinary or systems engineering models fail (Allison et al. 2018).

We believe that critical engagement with modeling for different aims of SESs research can contribute to developing integrative understanding and action toward enhanced resilience and sustainability. However, it is crucial that modeling is part of a larger process that involves, depending on the purpose, field studies, experiments, and participatory processes. Each part of the process highlights different aspects of the SES and involves different data and knowledge sources, and can thus jointly create a more differentiated and maybe adequate picture of the problem at stake. When based on the plurality of methods and applied in a larger process, modeling for SESs analysis, in our view, has the potential to significantly enhance the scientific basis for the governance of complex SESs and to support knowledge integration and social learning for the development of strategies and policies for SES governance. ModSES is a first step to encourage and provide guidance for the use of models and model-building processes involving modelers and nonmodelers as a tool to address sustainability problems in SESs.

Responses to this article can be read online at:
http://www.ecologyandsociety.org/issues/responses.php/10716

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Appendix for „The potential of models and modelling for social-ecological systems research – the reference frame MODSES"

Section 1: Selection of papers for review of resilience models (from 1998-2011)

We used the "Web of Science" database to identify relevant papers for our review. We searched for process-based modeling studies that dealt with resource management issues of social-ecological systems and were interested in resilience questions. We are aware that modeling studies that do not explicitly mention the term "resilience" but look at for instance "stability", "persistence" etc. may also contribute to resilience research. However in order to have a manageable number of papers we restricted the search to the term "resilience".

The exact query used was: **"TS=(resilience AND model AND ecol* AND (management OR resource OR governance))".** The search was carried out in April 2009 and repeated for papers from 2009 to 2011 in April 2012. 289 papers were detected by the search algorithm.

After reading the abstracts/the whole papers we eliminated those studies that did not fulfilled our criteria. For instance we did not want to investigate pure conceptual models which present only a system description or model framework without any model solution. Since we were interested in dynamic process-based models we excluded furthermore pure statistical models. Some of the studies presented a purely ecological model without any management or use - a further criterion for exclusion. Finally only 52 papers out of the 289 papers were left over for review (see below for a list of the papers). The years in which articles were published are depicted in Figure A1.

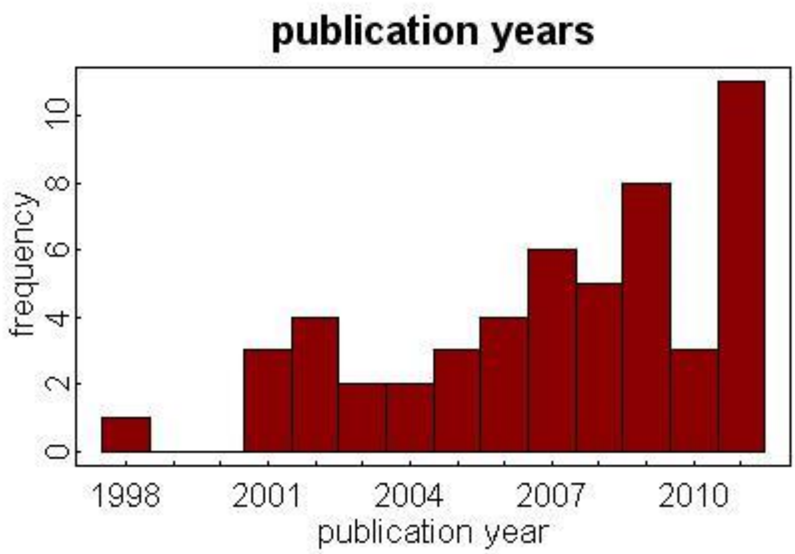

Figure A1: Years of publication

Papers included in review (from 1998-2011)

Albers, H. J.; Goldbach, M. J. & Kaffine, D. T. (2006), 'Implications of agricultural policy for species invasion in shifting cultivation systems', *ENVIRONMENT AND DEVELOPMENT ECONOMICS* **11**(4), 429-452.

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Section 2: List of categories used for the analysis of the published models (from 1998-2011)

Criteria describing field of application and model purpose

A Type of Ecosystem

1. rangeland
2. forest
3. coral reef
4. fisheries
5. lake eutrophication
6. agriculture
7. land management (general)
8. water management (general)
9. not specified

B Type of Social System

1. Single manager
2. Several managers not interacting with each other
3. Social manager
4. Network of actors
5. Actors not specified

C Model purpose

1. system understanding
2. forecasting or prediction (in quantitative manner)
3. management or decision support (in specific context, with management recommendations)
4. communication (to management)
5. learning (model used to change mental models)

Criteria describing model formulation, complexity and model solution

E Type of model

1. difference and differential equation model
2. rule-based model
3. state and transition model

F Model complexity

1. general model/conceptual model
2. site/context-specific

G Number of model parameters

1. low (<5)

2. medium (5<p<15)
3. high (>15)

M Dynamics

1. deterministic
2. stochastic

Criteria describing space and time

I Spatial Scale

1. local
2. regional
3. global

J Time

1. not dynamic
2. dynamic with continuous time
3. dynamic with discrete time

O Type of disturbance and change

1. variability in environmental variables
2. shocks in environmental variables (e.g. droughts)
3. changes in anthropogenic variables, e.g. management
   Note: More in the sense of abrupt shocks

P Feedbacks between social and ecological system

1. no
2. yes

Criteria which represent the link to real world and the level of integration

R Uncertainty

1. not considered
2. considered

T Model validation

1. no
2. yes

U Sensitivity analysis

1. no
2. yes

Z Model limits

1. discussed
2. not discussed

AA Link to “real world”

1. parameterized with empirical data
2. validated with empirical data / pattern
3. application for management discussed
4. no link

Criteria related to resilience theory

V Resilience concept

1. resilience = return time to equilibrium (“technical resilience”)
2. resilience = capacity of system to maintain structure and function when disturbed
3. other use of resilience term
4. not specified

W Resilience Mechanism

1. buffer in system structure
2. response diversity
3. functional diversity
4. heterogeneity
5. time lags
6. cross scale effect
7. adaptive capacity of management
8. others
9. not specified

X Measures of resilience

1. return time to equilibrium
2. size of basin of attraction
3. position of system in relation to threshold
4. performance indicators (productivity)
5. others
6. not specified

Y Additional considered aspects of resilience

1. adaptive cycle
2. panarchy (cross scale interactions)
3. adaptability
4. transformability
5. slow and fast variables
6. memory effect
7. thresholds

Section 3: Historical use of modeling in resilience research

Table A1: Results of the review of 52 models of resilience from 1998-2011

Study aims	Purpose of the model	# of papers	Key insights
Understanding SES persistence	System understanding Assessment of resilience of a specific system	**6**	Few models include feedbacks between social and ecological system Social system often not specified (e.g. only represented as variable that drives the ecological system)
	Identification of system characteristics and mechanisms that determine persistence • buffer • response diversity • governance or network structure • connectivity	**11**	
	Development of methods to operationalize and analyze resilience; predict critical transitions	**6**	
	Development of measures to quantify resilience or indicators of critical transitions	**5**	
Managing SES persistence	Decision/Management support Evaluation of management strategies	**13**	Lack of explicit links with real world (validation, uncertainty analysis, sensitivity analysis) Only few studies look at robust strategies
	• Explorative assessment of alternative management measures	10	
	• Assessing the tradeoff between resilience and economic productivity	3	
	Development of optimal management strategies	**7**	
Understanding and managing adaptation and transformation	Model purpose: System understanding Understanding adaptive capacity and traps	**4**	Only few studies address adaptation of social system to change No study addresses transformation

Detailed results of the review

Social-ecological systems considered and integration of the ecological and social subsystems

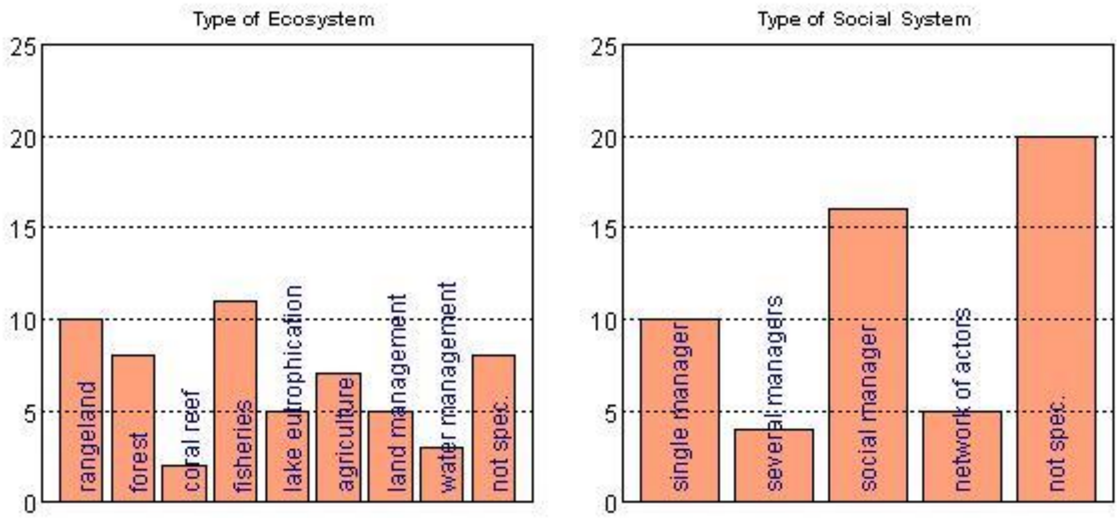

Figure A2: Ecological system/resource system (a) and social systems (b) regarded (Scale: number of papers out of all papers included in review (52))

The investigation shows that modeling studies about resilience have been developed for all different types of ecosystems or resource systems (rangeland, forest, coral reefs, fisheries, lakes, agriculture, land management and water management) (cf. Figure A2a). However, the social system is often not further specified (cf. Figure A2b), but rather represented as a change in a driving variable that is implicitly caused by change in management. Apart from that 31% of the studies assume a social manager and 19% a single one. Only in few cases a network of actors is considered (e.g. Bodin and Norberg (2005)).

The majority of studies (57%) consider feedbacks between social and ecological systems. However it is revealed that the inclusion of feedbacks varies for different model types: Social-ecological feedbacks are more present in the generic models (62%) compared to context-specific models (50%). Furthermore social-ecological feedbacks are more often included in models that apply differential or difference equations (64.0%) compared to rule-based (40%) and state and transition models (45%) (no figure).

Investigating whether disturbance is caused by anthropogenic or ecological variables the following results were depicted. In 25% of the papers disturbance was caused by variability in environmental variables, 35% caused by shocks in environmental variables and 69% caused by changes in anthropogenic variables (cf. Figure A3).

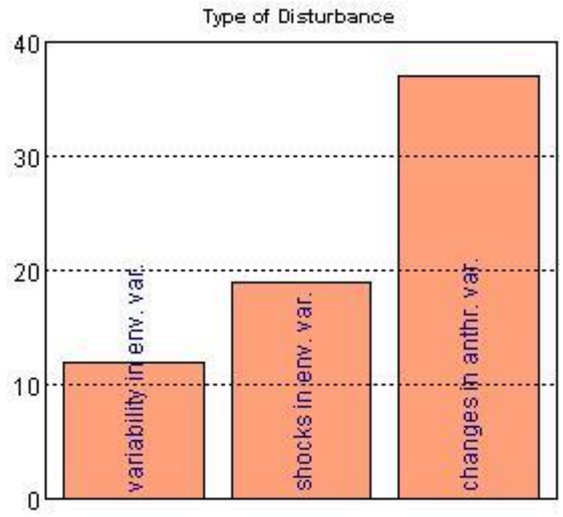

Figure A3: Types of disturbances represented in the models (Scale: number of papers out of all papers included in review (52))

Modelling techniques and system representation

Regarding the model type, the review process revealed that the majority (75%) of the studies used difference and differential equation to formulate the model, 19% used rule based models and 21% state and transition models (multiple answers possible, e.g. Bodin 2005 used differential equation to describe the ecological model and multi-agent simulation for the social system).

46% of the studies are stochastic. All models are formulated in a dynamic manner: 58% with continuous time, 42% with discrete time. From the spatial scale point of view: 67% addressed a local problem and 31% a regional. Two studies addressed a global scale.

Another focus of our review was set on whether the model built is context specific or is rather of general character (generic). The majority of the model studies used a generic model (67%). 35% of the models where context-specific (double entries were possible.) In a first specification, we wanted to investigate, whether a context-specific study uses another model description (rule-based vs. purely analytical) than a general one. Our review showed the following: Most general models were described by difference or differential equations (77%), secondly 18% by state-and transition models and 5% by rule-based models. Context-specific models are priorly formulated by rule-based models (38%) and 43% by equation-based approaches and 19% by state-and-transition models.

In a second specification, we wanted to investigate, if the utilization of context-specific vs. general model approach depends on the model purpose. We revealed the following: Models that address management issues, aim at forecast or support communication are rather context-specific than general and beside from that more complex (via number of parameters) compared to models with purpose understanding (Figures A4b, c). Consequently more than 50% of the management support models have high number of parameters, while most of the system understandings models have medium numbers. There are only very few models with a low number of parameters (in system understanding) (Fig. A4c).

A further difference in system representation depended on the modeled resource system: In rangeland, forest, fisheries, agriculture, land and water management there are both general and context-specific models. However for lake eutrophication, coral reef and studies where the type of ecosystem is not specified exclusively general models were used. Apart from coral reef, different all model types appear for the resource systems. State and transition models are not as common, mainly used in models about rangelands, forests and in models where the resource system is not specified.

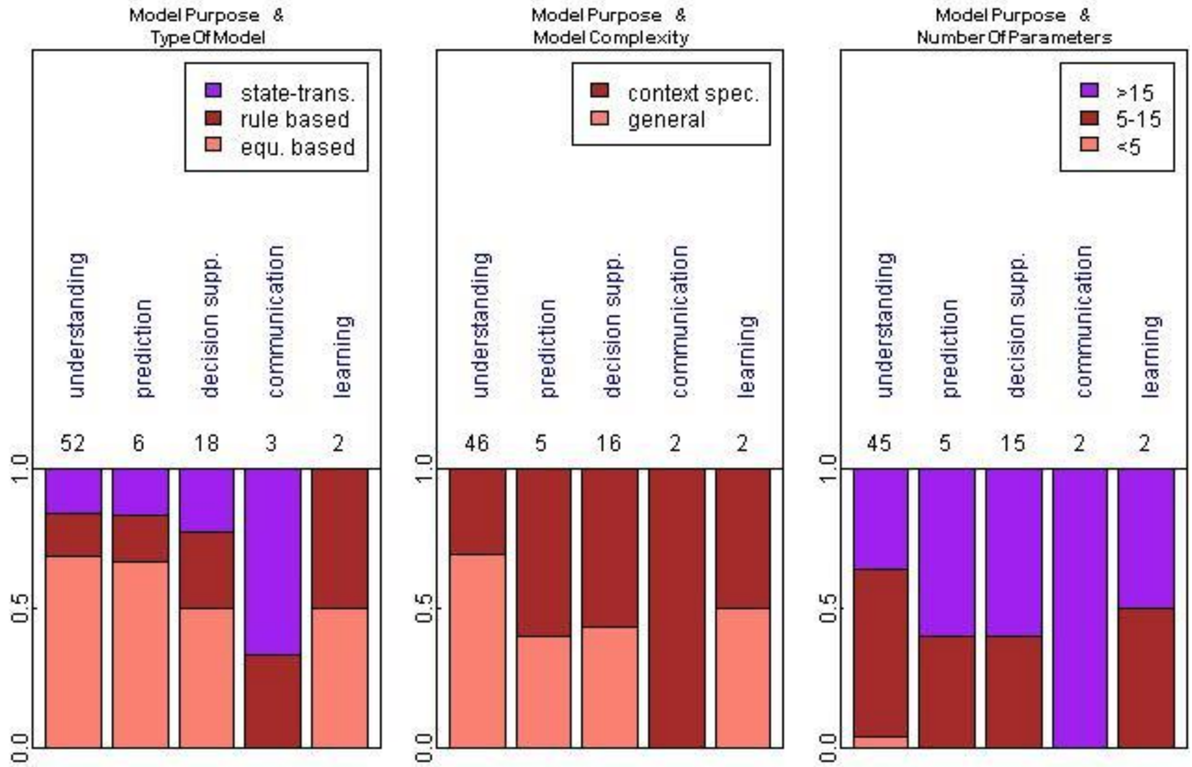

Figure A4: Relationship between model purpose and modeling technique (a) model type, b) model complexity and c) number of parameters used).