Title: Linking Model Design and Application for Transdisciplinary Approaches in Social-Ecological Systems

Authors: Cara Steger[a,b,c*], Shana Hirsch[d], Chris Cosgrove[e], Sarah Inman[d], Eric Nost[f], Xoco Shinbrot[g], Jessica P. R. Thorn[h,i], Daniel G. Brown[j], Adrienne Grêt-Regamey[k], Birgit Müller[l], Robin S. Reid[c], Catherine Tucker[m], Bettina Weibel[k], and Julia A. Klein[a,b,c]

*corresponding author: Colorado State University, Natural Resource Ecology Lab, Campus Delivery 1499, Fort Collins, CO 80523-1499. Email: Cara.Steger@gmail.com

a Graduate Degree Program in Ecology, Colorado State University, Fort Collins, CO. USA. 80523-1499. Cara.Steger@gmail.com; Julia.Klein@colostate.edu

b Natural Resource Ecology Laboratory, Colorado State University, Fort Collins, CO. USA. 80523-1499.

c Department of Ecosystem Science & Sustainability, Colorado State University, Fort Collins, CO. USA. 80523-1476. robin.reid@colostate.edu.

d Department of Human Centered Design and Engineering, University of Washington, Seattle, WA. USA. 98195. sinman1@uw.edu; slhirsch@uw.edu

e College of Earth, Ocean and Atmospheric Sciences, Oregon State University, Corvallis, OR. USA. 97331. cosgrovc@oregonstate.edu

f Department of Geography, Environment and Geomatics, University of Guelph, Guelph, ON. Canada. N1H 2W1. enost@uoguelph.ca

g Department of Natural Resources, Cornell University, Ithaca, NY 14853 xs364@cornell.edu

h York Institute of Tropical Ecosystems, University of York, Department of Environment and Geography, Wentworth Way, Heslington, York, North Yorkshire, YO10 5NG, UK jessica.thorn@york.ac.uk

i African Climate and Development Initiative (ACDI), University of Cape Town, Upper Campus, Geological Sciences Building Level 6, 13 Library Road, Rondebosch, 7700, Cape Town, South Africa jessica.thorn@act.ac.za

j School of Environmental and Forest Sciences, University of Washington, Seattle, WA. USA. 98195. danbro@uw.edu

k Planning of Landscape and Urban Systems, ETH Zurich, 8093 Zurich, Switzerland. gret@ethz.ch; weibel@nsl.ethz.ch l Department of Ecological Modelling, UFZ - Helmholtz Centre for Environmental Research, Permoser Str. 15, 04318 Leipzig, Germany. birgit.mueller@ufz.de

m Department of Anthropology, University of Florida, Gainesville, FL 32611. tuckerc@ufl.edu

Acknowledgements:

We are grateful to Dr. Anne Nolin, Dr. Arun Agrawal, and three anonymous reviewers for their suggestions on how to improve this manuscript. This work was supported by the US National Science Foundation through the Mountain Sentinels Research Coordination Network (NSF #1414106), the Swiss National Science Foundation through MtnPaths - Pathways for global change adaptation of mountain socio-ecological systems (#20521L_169916), and the Center for Collaborative Conservation at Colorado State University.

Abstract:

As global environmental change continues to accelerate and intensify, science and society are turning to transdisciplinary approaches to facilitate transitions to sustainability. Modeling is increasingly used as a technological tool to improve our understanding of social-ecological systems (SES), encourage collaboration and learning, and facilitate decision-making. This study improves our understanding of how SES models are designed and applied to address the rising challenges of global environmental change, using mountains as a representative system. We analyzed 74 peer-reviewed papers describing dynamic models of mountain SES, evaluating them according to characteristics such as the model purpose, data and model type, level of stakeholder involvement, and spatial extent/resolution. Slightly more than half the models in our analysis were participatory, yet only 21.6% of papers demonstrated any direct outreach to decision makers. We found that SES models tend to under-represent social datasets, with ethnographic data rarely incorporated. Modeling efforts in conditions of higher stakeholder diversity tend to have higher rates of decision support compared to situations where stakeholder diversity is absent or not addressed. We discuss our results through the lens of appropriate technology, drawing on the concepts of boundary objects and scalar devices from Science and Technology Studies. We propose four guiding principles to facilitate the development of SES models as appropriate technology for transdisciplinary applications: (1) increase diversity of stakeholders in SES model design and application for improved collaboration; (2) balance power dynamics among stakeholders by incorporating diverse knowledge and data types; (3) promote flexibility in model design; and (4) bridge gaps in decision support, learning, and communication. Creating SES models that are appropriate technology for transdisciplinary applications will require advanced planning, increased funding for and attention to the role of diverse data and knowledge, and stronger partnerships across disciplinary divides. Highly contextualized participatory modeling that embraces diversity in both data and actors appears poised to make strong contributions to the world's most pressing environmental challenges.

Keywords: Dynamic modeling; knowledge co-production; mountain social-ecological systems; mutual learning; transdisciplinarity; science and technology studies

1. Introduction

Social-ecological systems (SES) are facing unprecedented challenges from global environmental change (Turner et al. 2007). Responding to these changes is a central challenge for the management of sustainable ecosystems, with far-reaching consequences for human well-being (Lambin et al. 2001; Carpenter et al. 2009; DeFries et al. 2012). SES are characterized by complex processes with nonlinear dynamics, indirect effects and feedbacks, emergent properties, and heterogeneous links that extend across spatial and temporal scales (Liu et al. 2007). These characteristics can cause unanticipated outcomes that make environmental management difficult, particularly as decisions are often made in the context of limited data and high uncertainty (Polasky et al. 2011). Due to the complexity of SES, understanding global environmental change is critical for developing effective responses (Ostrom 2007, Turner et al. 2007, Lambin & Meyfroidt 2010).

As global environmental change continues to accelerate and intensify, science and society are turning to transdisciplinary approaches to facilitate transitions to sustainability (Lang et al. 2012; Brandt et al. 2013). Transdisciplinarity is a reflexive approach that brings together actors from diverse academic fields and sectors of society to engage in co-production and mutual learning, with the intent to collaboratively produce solutions to social-ecological problems (Cundill et al. 2015; Lemos et al. 2018; Wyborn et al. 2019; Norström et al. 2020). Such collaboration enables problems to be understood from multiple perspectives, and can expand the scope of potential solutions (Tengö et al. 2014; Hoffman et al. 2017; Chakraborty et al. 2019; Steger et al. 2020). This diversity also contributes to the perceived credibility, salience, and legitimacy of results (Cash et al. 2003; Cundill et al. 2015), empowering participants to take ownership of products and apply new knowledge to sustainability challenges on the ground (Lang et al. 2012; Balvanera et al. 2017).

Modeling is increasingly used by academics and development experts to encourage collaboration and learning among diverse groups to facilitate decision-making (Bousquet and Le Page 2004; Barnaud et al. 2008; Verburg et al. 2016; Voinov et al. 2018; Schlüter et al. 2019). While modeling may refer to any kind of qualitative or quantitative system representation used to identify and understand patterns or processes, in this study we explicitly focus on dynamic models showing change over time. Designing models that capture the complexity of SES while yielding useful information at relevant scales for management remains conceptually and methodologically challenging (Elsawah et al. 2019). SES modeling is often criticized for failing to address broader contexts: operating at too large a scale (O'Sullivan 2004; Mahony 2014), not representing or arbitrarily reducing complex processes to abstract quantities (Taylor 2005; Hulme 2011; Dempsey 2016; O'Lear 2016), or overlooking end-users' interests and capabilities (Rayner et al. 2005; Nost 2019). These critiques highlight the need for more widespread integration of transdisciplinary and co-production processes into SES modeling. Researchers have begun to formulate conceptual guides for transdisciplinary applications of SES models (Schlüter et al. 2019), though gaps remain in the development of theoretical and practical recommendations.

The purpose of this study is to understand how SES models are being designed and applied to the challenges of global environmental change and to develop guiding principles for transdisciplinary SES modeling. To limit the scope of the review, we analyzed 74 peer-reviewed papers describing applications of SES models in mountain areas. Mountains are a representative system for modeling dynamic processes in complex SES as they have high spatial and temporal heterogeneity and attract diverse actors with often conflicting worldviews and agendas (Klein et al. 2019; Thorn et al. 2020).

To analyze the design and application of SES models, we turn to Science and Technology Studies (STS) to conceptualize models as scientific artifacts (Latour 1986). The field of STS has long advanced the social study of science, illustrating how material devices (Latour 1986), embodied practices (Haraway 1988), and infrastructures (Bowker and Star 1999) shape knowledge production. Here, we focus on models as knowledge infrastructures, which Edwards et al. (2013) define as "robust networks of people, artifacts, and institutions that generate, share, and maintain specific knowledge about the human and natural worlds" (p. 23). We draw on three concepts related to knowledge infrastructures to analyze the design and application of SES models: appropriate technology (Fortun 2004), boundary objects (Star and Griesemer 1989), and scalar devices (Ribes 2014). We use these concepts to explore how SES models influence collaboration around environmental problems (Taylor 2005; Sundberg 2010; Landström et al. 2011), shaping the production of new knowledge, relationships, and decisions.

1.1 Conceptual framework: SES models as appropriate technology for transdisciplinary applications

Scholars are calling for a more reflexive consideration of models' embeddedness in socio-cultural contexts and relevance for particular places and problems (Taylor 2005; Crane 2010). The concept of appropriate technology broadens our view beyond the technical correctness of models, towards this more societal focus. Appropriate technology emerged from alternative technology movements of the mid-twentieth century, and refers to tools, techniques, and machinery used to address livelihood and development problems in ways that are sensitive to place-based needs, as opposed to one-size-fits-all solutions. STS researchers have applied the concept to other contexts, such as questioning how scientists acquire "the right tools for the job" (Clarke and Fujimura 1992; de Laet and Mol 2000). Following Fortun (2004), an SES tool such as simulation modeling could be considered appropriate technology when it is "designed in a way attuned to the material, political, and technological realities with which it works, and to the social actors who will be its users" (p.54). For example, Fortun (2004) describes the development of a publicly-available pollution database and website in the early 2000s, which allowed the public to search for toxic releases by company name and to learn about subsequent risks to human and environmental health. This website was appropriate technology for the time given that key aspects to US environmentalism were open source technologies, corporate transparency, and complexity science.

In this paper, we examine whether SES models are appropriately designed for contemporary transdisciplinary applications that aim to understand and overcome the challenges presented by global environmental change. These challenges demand societally-relevant integration of data and stakeholder perspectives across spatial and temporal scales, yet this is difficult to accomplish due to: (1) diverse and sometimes contradictory stakeholder objectives and worldviews (Etienne et al. 2011; Etienne 2013; Lade et al. 2017), including epistemological rifts between the socio-cultural and computational sciences that prevent detailed representations of social processes in SES models (Taylor 2005; Crane 2010; Verburg et al. 2016; Voinov et al. 2018); and (2) mismatching scales of social and ecological processes and associated data (Zimmerer and Basset 2003; Cumming et al. 2006; Bakker and Cohen 2014; Rammer and Seidl 2015; Lippe et al. 2019). By employing the conceptual framework of models as "appropriate technology," our evaluation focuses on how SES models span social boundaries and spatial scales. We use the concepts of "boundary objects" and "scalar devices" to explore how SES models bring together diverse groups of people with the aim of improving understanding and management of SES (boundary objects, section 1.1.1), and how SES models can help understand cross-scale and cross-level dynamics (scalar devices, section 1.1.2). We propose that SES models that achieve these dual objectives can best function as appropriate technology (Figure 1).

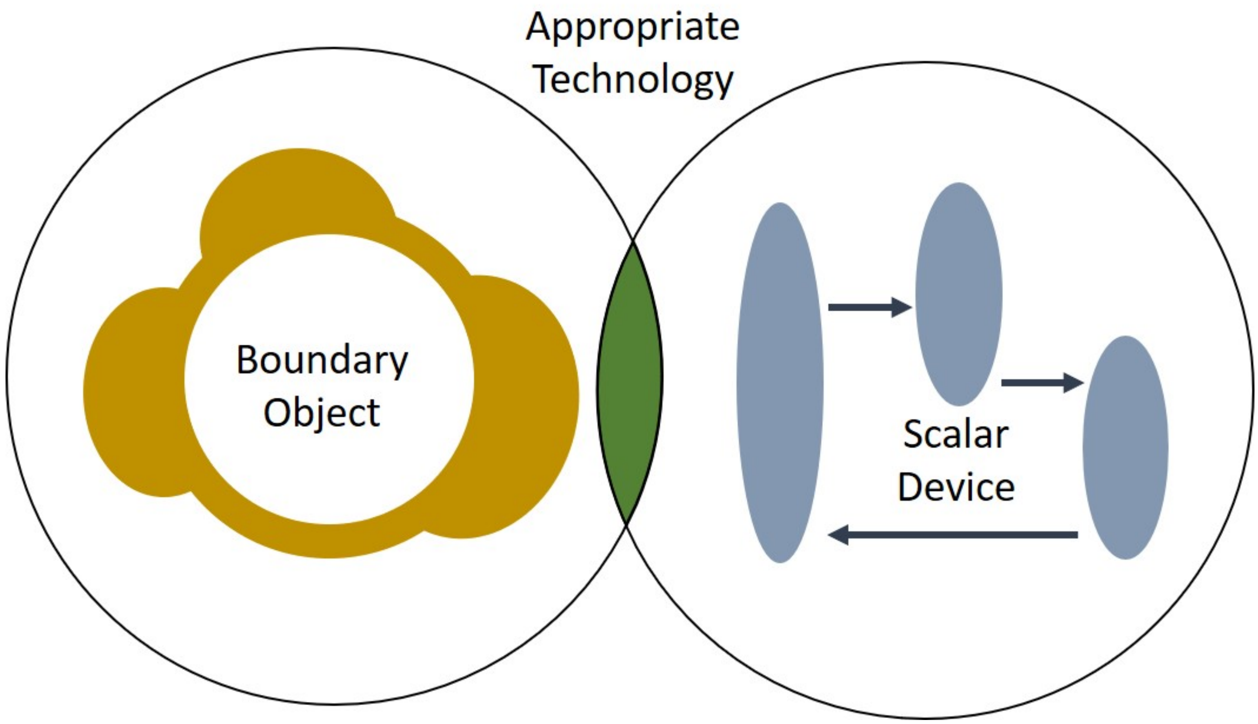

Figure 1. Conceptual relationship between boundary objects and scalar devices, indicating that SES models may function as appropriate technology for transdisciplinary applications when they simultaneously span social boundaries and spatial scales (green area).

1.1.1 Models as boundary objects

Traditionally, model design has been the purview of scientific research communities. However, recent attempts to incorporate more diverse stakeholder perspectives have led to the co-design of SES models, allowing for different understandings, values, and worldviews to be elicited, visualized, and negotiated in the pursuit of a shared "boundary object" or system representation (Zellner 2008; Etienne et al. 2011; Etienne 2013; Edmonds et al. 2019). Boundary objects are conceptual or material items that emerge through collaboration, remaining both adaptable to local needs yet "robust enough to maintain a common identity" across different groups (Star and Griesemer 1989, pg. 393). Stakeholders can hold different, sometimes conflicting, ideas about boundary objects yet still collaborate through them. One example, described by Star and Griesemer (1989), includes a bird in a natural history museum: the specimen carried different value and meaning to amateur bird watchers, professional biologists, and taxidermists, who worked together using the boundary object while maintaining different epistemic perspectives. In this way, boundary objects enable people to work together across knowledge systems despite syntactic and semantic differences in understanding (Carlile 2002), illustrating how collaboration can occur without requiring consensus.

The boundary object concept has been widely applied outside STS given its utility in understanding the process of collaboration in inter- and trans-disciplinary settings (Clark et al. 2011; Steger et al. 2018). Here, we examine how SES models can function as boundary objects for transdisciplinary work, exploring how a model can span multiple social worlds beyond one system or knowledge type (Clarke and Star 2008).

1.1.2 Models as scalar devices

A core challenge of modeling SESs is the scalar mismatch (Zimmerer and Bassett 2003) occurring between social and ecological processes and the data that represent them (Walker et al. 2004; Cumming 2006; Rammer and Seidl 2015). For example, models that forecast regional climate change may not have adequate spatial resolution to incorporate local level human drivers like land use change, yet it is the combination of these multi-scalar drivers that could pose the highest risk and uncertainty for the system (Altaweel et al. 2009). Efforts to address these scalar issues are limited by computing power, data availability, and the ability to make inferences from highly complex or complicated models (Kelly et al. 2013; Verburg et al. 2016; Lippe et al. 2019). Here, we examine how models are used as “scalar devices” to conceptually shift between temporal or spatial scales, thus aiding users in overcoming this scalar mismatch.

Ribes (2014) proposed the ethnography of scaling as a methodological approach for studying long-term scientific enterprises, where scalar devices are the tools and practices researchers use to represent, understand, and manage large-scale objects or systems that cross multiple levels of organization (Ribes and Finholt 2008). For example, Ribes examines how scientists used agendas, slides, and notes as scalar devices to summarize current and future disciplinary needs across multiple scales when creating the geosciences network known as GEON. These tools condensed months of work across disparate groups of scientists into concrete objects and representations that could be examined and questioned within the same room at the same time, thus translating a large and complex system into a more approachable format. Scalar devices can also refer to social activities such as all-hands meetings that bring together networks of people to deliberate and communicate about large-scale spatial and temporal dynamics. In this paper, we conceptualize SES models as scalar devices to understand how they are used to isolate certain components and feedbacks in SES so that these systems might be more clearly understood, predicted, and managed across scales.

Below, we describe patterns in how SES models are designed and used to address cross-disciplinary and cross-scalar processes. We draw on these results to re-examine our conceptual framework (Figure 1) that places appropriate technology for SES modeling at the intersection of the boundary object and scalar devices concepts. In light of these results, we propose a set of guiding principles to facilitate the development of SES models as appropriate technology for transdisciplinary applications.

2. Materials and Methods

2.1 Search strategy

We reviewed literature employing dynamic social-ecological models in mountain systems, searching combinations of keywords in the search engine Google Scholar (model*; 'coupled human natural systems' or 'coupled natural human systems'; 'social-ecological systems' or 'socio-ecological systems'; 'change'; 'management'; 'mount*' or 'highland' or 'alpine'). Keywords were compiled during meetings with experts from the Mountain Sentinels Collaborative Network (mountainsentinels.org), a group of researchers and other stakeholders working towards mountain sustainability worldwide. We expanded this search by following references included in these papers to other studies and via consultations with experts. All papers published in English prior to August 2017 were considered for inclusion if they contained one overarching modeling effort, which in some cases consisted of multiple modeling approaches either integrated or presented alongside one another. To be included, models needed to be dynamic (showing change over time) and include both social and ecological components. Although this search was not systematic, the 74 papers we reviewed represent a significant proportion of the literature available.

2.2 Data collection

Each of the 74 papers (Appendix A) was coded independently by two team members according to a codebook developed and tested on five papers. Differences were discussed and resolved by a third reviewer as needed. We operationalize the concept of appropriate technology by assessing characteristics of SES model design and application, including the model purpose, stakeholder involvement, and spatial extent/resolution (Table 1). We use these codes as "sensitizing concepts" (Blumer 1954) to guide our exploratory analysis and to conceptually bridge between measurable SES modeling characteristics and the relative ambiguity of the STS concepts we described above.

Design codes	**Description**	**Measurement**	**Appropriate Technology**

Model purpose (intended)	System understanding; prediction and forecasting; decision support; and communication/learning (Kelly et al. 2013)	Not addressed / secondary purpose / primary purpose	Scalar devices Boundary objects
Model specificity	Level of context-specificity and level of generalizability	None/low/medium/high	Scalar devices
Model orientation	Level of scientific orientation and level of societal orientation	None/low/medium/high	Boundary objects
Model types	Agent-based, integrated simulation, systems dynamics, Bayesian Network, cellular automata, mathematical, statistical, or GIS	Present or absent	Scalar devices Boundary objects
Data types	Biophysical (e.g. climatic, ecological, hydrological, geologic/topographic) Social (e.g. economic, political, demographic, ethnographic) Social-Ecological (e.g. land use or livelihoods)	Present or absent	Boundary objects Scalar devices
Model extent	Social	The broadest organizational level addressed: individual, household, community,	Scalar devices

	Spatial	region, nation, multi-nation, or global The size of the study area (e.g., km^2) where available	
Model resolution	Social Spatial	The narrowest organizational level addressed: individual, household, community, region, nation, multi-nation, or global The size of the smallest pixel or modeling unit (e.g., km^2) where available	Scalar devices
Public participation	Whether or not non-researchers were involved in modeling	Present or absent	Boundary objects
Stakeholder diversity	What level of stakeholder diversity was present in the system being modeled	Not mentioned/none/low/high	Boundary objects
Application codes			
Model purpose (achieved)	System understanding; prediction and forecasting; decision support; and communication/learning (Kelly et al. 2013)	Not addressed / secondary purpose / primary purpose	Scalar devices Boundary objects
Policy or planning outreach	Whether or not modeling results were communicated to	Present or absent	Boundary objects

	decisionmakers (e.g., policy makers, planners, managers)		

Table 1. Codebook organization.

Design codes focused on the methods used to build the models. Model types included eight non-mutually exclusive categories each study could include: agent-based, integrated simulation, systems dynamics, Bayesian network, cellular automata, mathematical, statistical, and GIS. We also noted whether toy models or role-play games were used to engage participants. Data types were coded into: “biophysical”, “social”, or “social-ecological” categories, which were further specified into sub-categories (Table 1). We drew on the data types used to understand how models act as boundary objects by integrating diverse perspectives through data, and what kinds of data are most frequently applied to model cross-scale dynamics. See Appendix B for detailed definitions of data and model types.

Coders identified information on the social and spatial scale of the models, which we used to assess how models function as scalar devices. We divided these data into extent (broadest level) and resolution (narrowest level). We classified social scale according to the organizational or administrative levels addressed in the model (Gibson et al. 2000; Cash et al. 2006; Preston et al. 2015), organizing them into seven qualitative and hierarchical categories: individual, household, community, region, nation, multi-nation, or global. We determined whether a model considered cross-scale processes by calculating the number of social levels crossed between the extent and resolution of the model. For example, a model that crossed two scales might go from a regional-level extent to a household-level resolution. We also recorded the quantitative size of the study area (extent) and the size of the smallest pixel or unit of the model (resolution), when available.

The level of model specificity was assessed via two questions regarding the degree of a) contextual understanding and b) general, transferable understanding emphasized in the model development and application. Contextual and general understanding were ranked independently of one another (Table 1; none/low/medium/high), contributing to our understanding of how SES models act as scalar devices. A highly contextual model presented a detailed description of the study site and clarified how this context influenced model design and application, while a highly generalizable model explicitly and repeatedly emphasized how their modeling effort was relevant to other systems. Similarly, the theoretical orientation of the model was assessed via two questions (ranked independently) regarding the advancement of a) theoretical/scientific knowledge and b) societal goals/processes. According to our rubric, a highly scientifically-oriented model clearly advanced some research field or theory, while a highly societally-oriented model supported a social objective or laid the foundation for locally-relevant decision-making (e.g., policy making, management action, planning processes, educational tools). Thus the orientation of the model sheds light on how these models function as boundary objects. These four questions allow us to determine which models were both highly contextual and also highly generalizable to other systems, or which models managed to achieve high scientific as well as high societal relevance.

Coders extracted all textual references to public participation, which included the involvement of any non-researcher stakeholder group. These data were categorized into a binary participatory or non-participatory variable. Any level of engagement with the public - from model conceptualization, design, development, or implementation - was considered participatory. Stakeholder diversity was another variable that was either not mentioned in the paper, or coded as none, low, or high levels of diversity. Together these variables clarify the diversity of people involved in the modeling activity, an important criteria for functioning as a boundary object.

Model purpose refers to the goals of the modeling work and were adapted from Kelly et al. (2013) to include: system understanding, prediction/forecasting, decision support, and learning/communication (see Appendix B). We define the learning/communication purpose as a contribution towards "the capacity of a social network to communicate, learn from past behaviour, and perform collective action" (Kelly et al. 2013, pg. 161), which distinguishes it from more general system understanding. Models designed for decision support include a wide variety of decision contexts, including multi-criteria analyses, trade-offs in decision-making, land use planning, and management actions. Coders recorded the intended model purpose and classified whether each intention and outcome was addressed as a primary or secondary purpose of the project. We used quotations from the text to resolve any differences between coder ranking. Due to this potential subjectivity, and sometimes small sample sizes, we treated the model purpose variables as binary Yes (primary or secondary purpose) or No (not addressed) in most of our analyses. Finally, coders extracted all references to policy and planning outreach, which we translated into a binary code indicating whether or not the model or study results were directly communicated to decision makers.

2.3 Analysis

We present summary statistics that describe trends in SES modeling design and application. We use chi-square or Fisher's exact tests and t-tests as relevant to look for associations between model purpose outcomes and the various design codes described above. For all tests, we consider $p<0.05$ to be statistically significant.

3. Results

3.1 Model purpose: Intention vs. outcome

Many studies successfully achieved the outcome they intended (Figure 2). Almost three-quarters (73%) of the papers intended system understanding to be a primary purpose of the model (n=54), yet only 57% (n=42) achieved it as a primary outcome. Instead, most of these papers achieved secondary system understanding outcomes. Prediction/forecasting was not a frequent primary model purpose (n=21, 28%), but was commonly considered a secondary model purpose (n=35, 47%). There was little difference between intentions and outcomes for the prediction/forecasting purpose, indicating these SES models generally achieved their intended purpose. These model purposes require integrating information about the world across different geographic levels and multiple time horizons, thus aligning with the scalar devices concept.

There was considerably greater difference between intentions and outcomes for both decision support and learning/communication model purposes (Figure 2), indicating that SES models may face barriers when created for these purposes. Decision support was commonly intended as a primary model purpose (n=35, 47%). However, almost half of the papers that intended decision support as a primary purpose instead achieved it as a secondary purpose (n=16), and 44% of the papers that intended it as a secondary purpose failed to report any successful decision support outcomes (n=11). Most papers we reviewed did not consider learning/communication to be an intended model purpose (n=46, 62%). Nevertheless, 39% of the papers that intended it as a secondary purpose failed to report any learning/communication outcomes (n=7), while the same number of papers discovered unexpected learning outcomes despite having no intention of it. These results point to gaps in the ability of SES models to contribute to decision support outcomes, and a general inattention to learning/communication model purposes. These model purposes are aligned with the boundary object concept as they typically rely on significant stakeholder engagement. The fact that their intended use fell short of their realized use suggests critical gaps in the role of SES models as boundary objects.

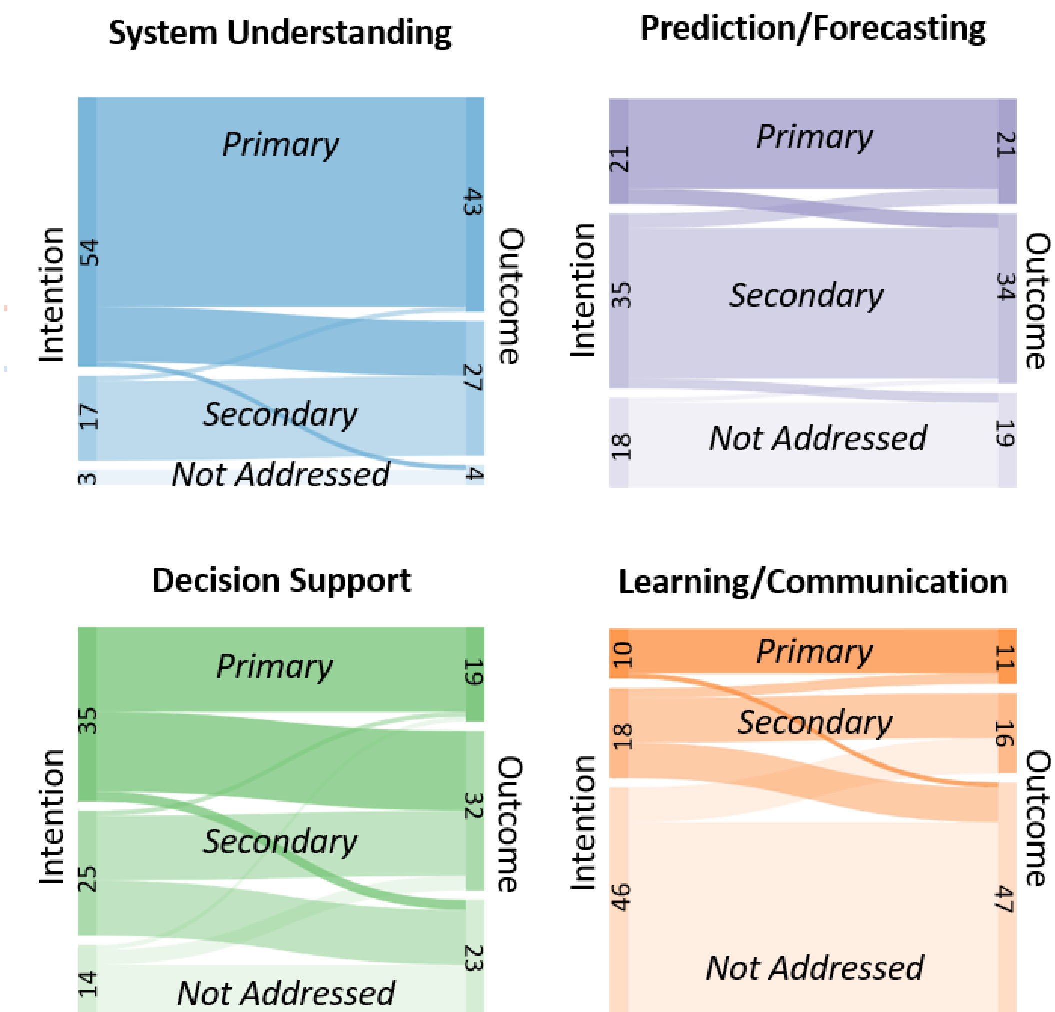

Figure 2. Number of papers per model purpose, for both intentions and outcomes.

3.2 Model specificity and orientation

Most models (n = 47, 63.5%) had a highly context-specific focus, while only 10.8% (n=8) were considered highly generalizable, illustrating a preference for SES models to focus on particular places and their relevant scales of operation rather than generic systems or processes. Most models (n=40, 54%) were also classified as having medium scientific orientation. While scientific or theoretical advancement was a common goal of SES modeling efforts, there was less consistency for societal goals, as models were roughly evenly distributed across low, medium, and high levels of societal orientation. These results again highlight potential gaps in how SES models are used as boundary objects. When analyzing the relationship between model specificity and orientation, our results indicated that SES models used to advance societal goals also tended to be highly context specific ($p<0.01$; Figure 3a), while scientific goals appeared to be advanced even at low or nonexistent levels of system-specific context ($p=0.02$; Figure 3b). This points to potential synergies between the STS concepts, where SES models are more likely to function as boundary objects (i.e., by advancing societal goals) when they are created at scales relevant to a particular context.

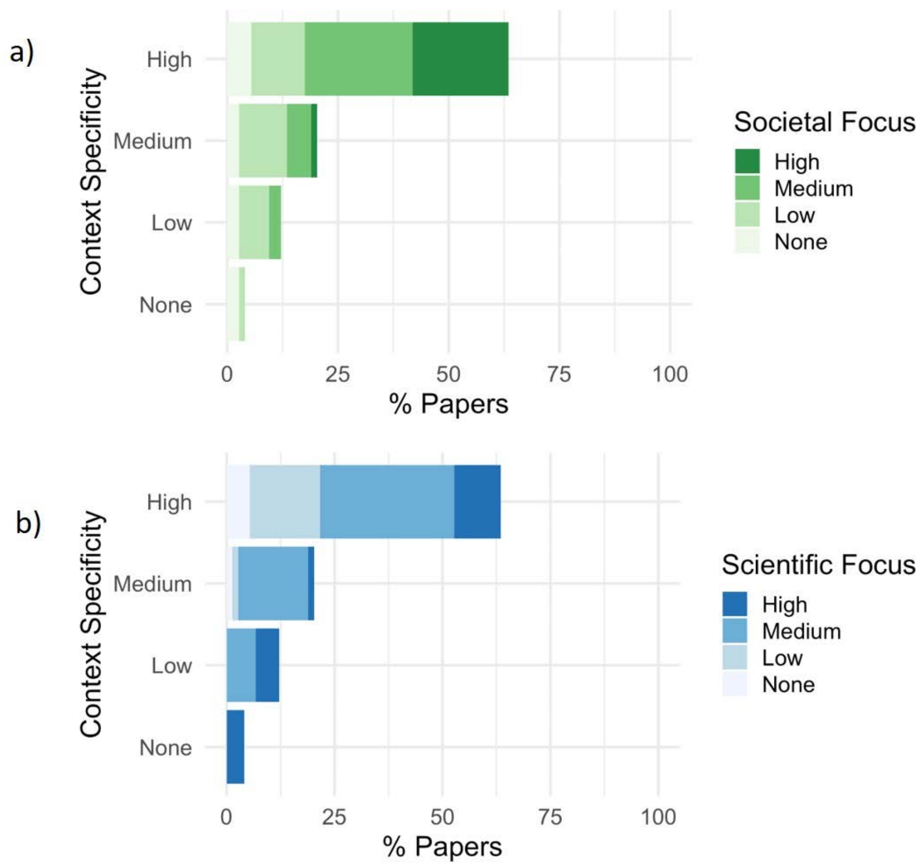

Figure 3. Percent of papers per level of context-specificity, according to a) societal orientation and b) scientific orientation.

We found significant associations between learning/communication outcomes and context-specificity ($p < 0.00$), where most models with learning outcomes were also highly context-specific (n=24, 89%; Figure 4a). This indicates that context specificity is an important characteristic of SES models that function as boundary objects, perhaps by enabling stakeholders to recognize and relate to the system represented. Learning outcomes also occurred with more regularity across medium to high levels of societal orientation ($p < 0.00$; Figure 4b), supporting the idea that societally-oriented models are more likely to function as boundary objects. Decision support outcomes were highest at low to medium levels of generalizability ($p = 0.04$; Figure 4c) and almost non-existent when the models lacked societal orientation ($p < 0.00$; Figure 4d). This suggests there was some flexibility in achieving decision support outcomes; if modeling efforts included a modest degree of generalizability and societal focus, decision support outcomes tended to occur. However, both learning and decision support outcomes were most common at medium to high levels of societal orientation, indicating that the pursuit of these model purposes may promote the use of SES models as boundary objects.

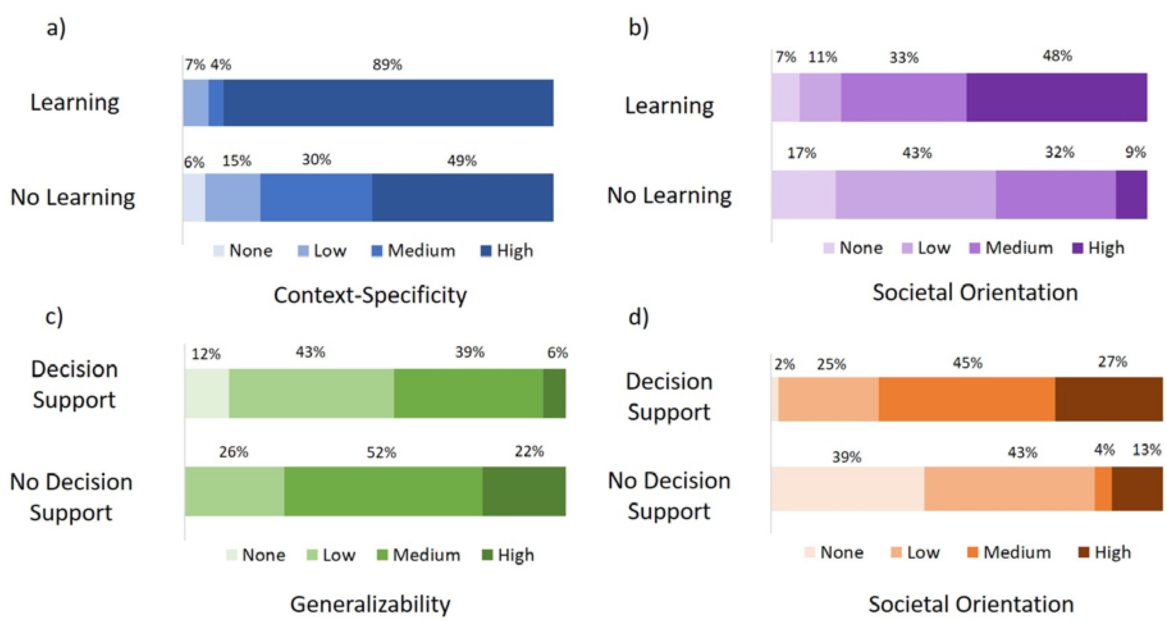

Figure 4. Model purpose outcomes were significantly associated with the context-specificity, generalizability, and societal-orientation of the models.

3.3 Model types

Of the eight model types, agent-based models (ABM) were the most frequently used (n = 48, 64.8%), followed closely by cellular automata models (n = 46, 62.1%). In fact, ABM and cellular automata models were used together in almost half the studies (n = 36, 48.6%), though decision support outcomes were more common when cellular automata models were absent ($p = 0.02$). Mathematical models were also relatively common (n=34, 45.9%). Learning outcomes were significantly higher when toy models or role-play games were used ($p < 0.01$), indicating that models built with stakeholder involvement in mind tended to function as boundary objects. No other model types were associated with higher model purpose outcomes.

Studies used one modeling approach (n =11, 14.8%), or combined two (n=30, 40.5%), three (n=21, 28.3%), or four (n=12, 16.2%) modeling approaches to represent and scale the system in different ways. When only one modeling approach was used, system dynamics and mathematical models were most frequent. When multiple approaches were used, ABM and cellular automata models were most frequent. We did not find any associations between model purpose outcomes and the number of modeling approaches used.

We did not find significant associations between model type and scientific orientation, though mathematical models and system dynamics models do have significant associations with societal orientation. Specifically, mathematical models were more likely than non-mathematical models to have intermediate (low or medium) levels of societal orientation ($p<0.00$). We also observed a higher proportion of system dynamics models with high societal orientation (71%), compared to only 18% of non-system dynamics models ($p=0.01$). This suggests that system dynamics and mathematical models tend to be used as boundary objects. We did not find any associations between model type and model specificity, indicating that the type of modeling approach is unrelated to the context-specificity or generalizability of the model. Together, these results demonstrate that the question of model type is related more to the role of the model as a boundary object rather than as a scalar device.

3.4 Data types

We found that SES models tend to under-represent social datasets, and are more likely to rely on pre-existing datasets. Models used significantly higher numbers of biophysical ($\mu = 5.0$, SE± 1.2, $p < 0.00$) and social-ecological ($\mu = 4.3$, SE± 0.9, $p = 0.04$) datasets compared to social datasets ($\mu = 3.4$, SE± 0.8). The similar number of biophysical and social-ecological datasets suggests these data types are roughly equally valued for representing dynamic SES. However, the relative lack of social datasets may point to gaps in how SES models span multiple social worlds. For all data types, secondary datasets (e.g., from the literature or published data) were significantly more common than primary datasets collected from the study site. The most common datasets were ecological (median = 2), followed by land use (median = 1.5) and demographic, economic, climatic, geologic/topographic, and SES livelihood datasets (median = 1). Meanwhile political, ethnographic, and hydrologic datasets were infrequently included in models (median = 0).

Our results point to potential tradeoffs between the number of biophysical datasets used and model purpose outcomes related to system understanding and learning/communication. Models with system understanding outcomes used significantly higher numbers of biophysical datasets ($u = 5.1$) than those without understanding outcomes ($u = 2.8$, $p < 0.02$). However, models with learning outcomes used significantly fewer biophysical datasets ($u = 3.7$) compared to those without learning outcomes ($u = 5.7$, $p < 0.00$).

3.5 Extent and resolution

Most models had social extent at the regional and community levels and social resolution at either the household or individual level (Figure 5). No models had coarser than a regional resolution. We grouped models according to small or large social extent as well as fine or coarse social resolution, and found no association with model purpose outcomes. We examined patterns between social and spatial scale, finding that regional-level extent corresponded to an average study area of 10,815 km^2 (SE± 4,855 km^2) and community-level extent had an average study area of 385 km^2 (SE± 348 km^2). We also found the average resolution was 0.54 km^2 (SE± 0.31 km^2) for household-level models, and 0.22 km^2 (SE± 0.09 km^2) for individual-level models. However, quantitative information was only provided by 69 papers (93%) for spatial extent and 56 papers (76%) for spatial resolution. These results shed light on how SES models act as scalar devices by integrating information across different geographic scales into more compressed representations of the system.

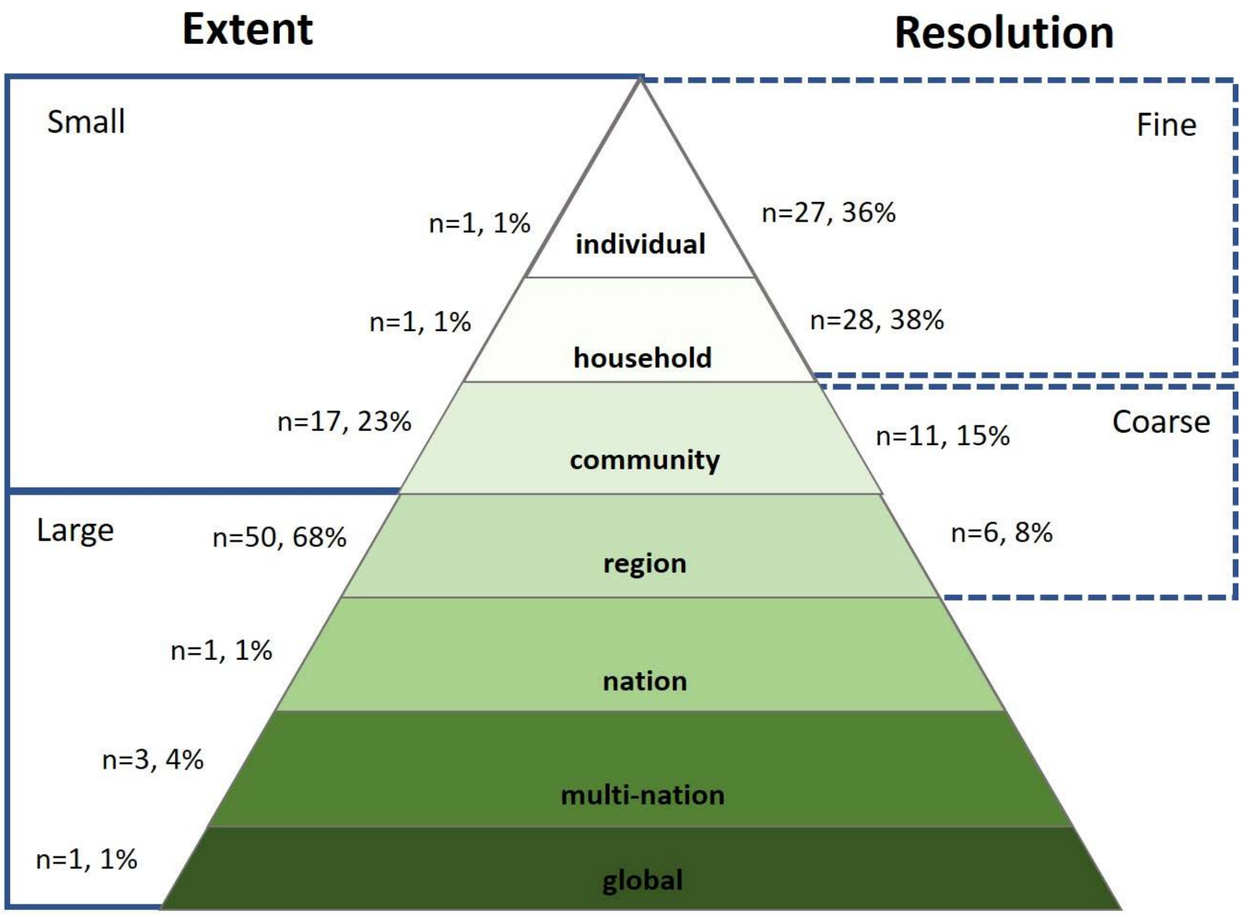

Figure 5. The number and percentage of models at each extent and resolution level.

Only seven models in our review focused on a single scale (i.e., had the same extent and resolution), and these were found across all model types except toy models (Figure 6). Models crossed either one (n=17, 23.0%), two (n=31, 41.9%), three (n=13, 17.6%), four (n=2, 2.7%), or five (n=2, 2.7%) scales. Bayesian networks tended to maintain the same extent and resolution (i.e., were not cross-scalar), and system dynamics models were most likely to cross just a single scale. Of all the model types, only ABMs, ISMs, and mathematical models were observed to cross five spatial scales between their extent and resolution. We examined whether the number of scales crossed between extent and resolution impacted model outcomes, but found no significant associations. These results indicate that certain model types may be more useful than others for representing highly cross-scalar dynamics. However, the number of scales crossed is not by itself an adequate measure of what constitutes a scalar device, because a higher number of scales crossed does not appear to support higher model purpose outcomes.

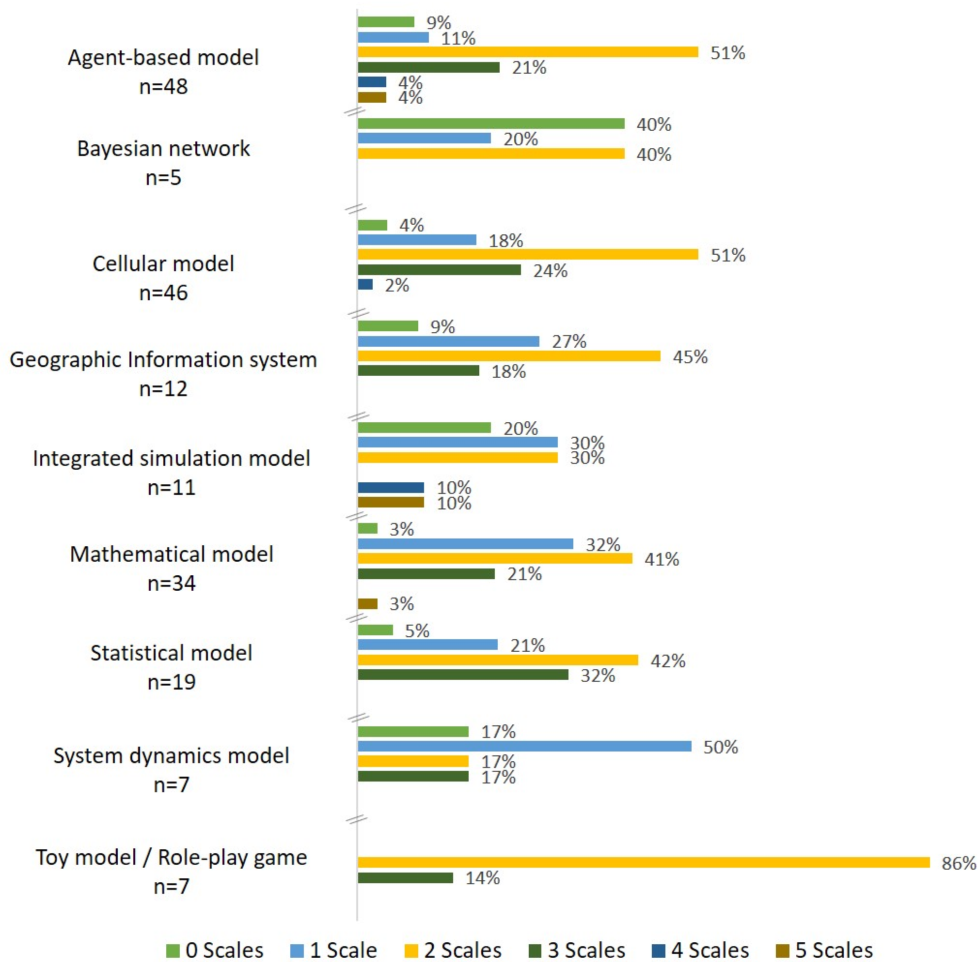

Figure 6. The proportion of each model type according to the number of scales crossed.

3.6 Public participation, stakeholder diversity, and policy or planning outreach

Roughly half the models in our analysis were participatory (n = 38, 51.4%). However, only 21.6% (n = 16) demonstrated any direct outreach to decision makers (e.g., through a presentation of results or workshop). We found higher learning outcomes in participatory models ($p < 0.00$) and models with policy or planning outreach ($p < 0.00$). While not significant, decision support outcomes were also more likely with participatory models (n=30, 79%) compared to non-participatory models (n=21, 58%). Perhaps unsurprisingly, we found a strong association between decision support outcomes and models with policy or planning outreach ($p < 0.00$). Finally, we found a significant association between outcomes of decision support and levels of stakeholder diversity, indicating that modeling efforts where stakeholder diversity is present tend to have higher rates of decision support compared to situations where stakeholder diversity is not present or not addressed. Together, these results support our characterization of SES models as boundary objects that invite successful collaboration (i.e., learning or decision support) between diverse actors who may not otherwise agree.

4. Discussion

This study improves our understanding of how SES models are designed and applied to address the rising challenges of global environmental change, using mountains as a representative system. In this section, we discuss the results outlined above by drawing on the concepts of boundary objects and scalar devices to understand how SES models operate as appropriate technology (Table 1, Figure 1). While we initially proposed that appropriate technology for SES modeling would sit at the intersection of boundary objects and scalar devices, our results stress the importance of SES models functioning as boundary objects for effective transdisciplinary work to occur. Meanwhile, crossing multiple temporal and spatial scales was less critical for appropriate SES modeling, and we encourage modelers to instead remain flexible and sensitive to end user needs and contexts when designing models. We propose four guiding principles to facilitate the development of SES models as appropriate technology for transdisciplinary applications: (1) increase diversity of stakeholders in SES model design and application for improved collaboration, (2) balance power dynamics among stakeholders by incorporating diverse knowledge and data types, (3) promote flexibility in model design, and (4) bridge gaps in decision support, learning, and communication.

4.1 Increase diversity in SES model design and application for improved collaboration

We found that models incorporating diverse stakeholders through public participation and policy outreach act as transdisciplinary boundary objects by supporting higher learning and decision support outcomes. For example, Anselme et al. (2010) used an agent-based model to better understand and manage high biodiversity habitats threatened by shrub encroachment in the French Alps. Through this collaborative process, a forest manager came to appreciate the need for genetic diversity in the forest stands he was managing, leading him to support the development of a "genetic quality index" to better enable managers and scientists to work together. Despite strong learning outcomes, stakeholders in this process remained skeptical about their ability to influence policy formation at higher levels. Smajgl and Bohensky (2013) took a more targeted approach to influencing policy in their spatial modeling of poverty in East Kalimantan, Indonesia. They worked directly with government decision-makers to determine the optimal level for petrol prices that would enable more citizens to engage in high-income, petrol-dependent livelihoods like fishing and honey collection. While both of these participatory examples had high outcomes of both decision support and learning/communication, they differed in the degree to which they targeted specific policy decisions - indicating that policy outcomes are not necessary for SES models to function as boundary objects.

Models used in conditions of high stakeholder diversity tended to yield higher decision support outcomes compared to models where stakeholder diversity was not present or not addressed. While it might be expected that situations bringing together people from diverse backgrounds and perspectives would be a source of conflict, examining these results through the lens of boundary objects highlights how SES models can work across scientific and social worlds to promote collaboration without requiring consensus. For example, Barnaud et al. (2013) examined an agent-based model in the context of conflicting ecological, economic, and social interests among stakeholders involved in land management in Northern Thailand. The collaborative modeling process encouraged stakeholders to reframe their approach to the conflict and "move from a distributive to an integrative model of negotiation" (pg. 156) by setting aside the question of park boundaries for a time and instead focusing on a more integrated understanding of the system as represented through the model. This enabled them to find potential synergies rather than focusing on the conflicting interests of the different groups, suggesting the process of creating and using models as boundary objects can encourage diverse stakeholders to move past underlying disagreements and develop workable solutions.

Overall, participatory models were strongly represented in our review, indicating that these approaches are no longer on the periphery of SES modeling practice in mountains. We find similar patterns throughout the literature (Voinov and Bousquet 2010; Gray et al. 2017; Jordan et al. 2019), indicating that the field of participatory modeling is maturing rapidly in non-mountain systems as well. Whether by design or not, some SES models have functioned as boundary objects by enabling the integration of diverse perspectives without sublimating them. Diverse perspectives are at the core of transdisciplinary work, as multiple viewpoints, epistemologies, and values are needed to holistically understand complex SES problems and devise solutions with high relevance (Bernstein 2015; Hoffman et al. 2017; Norström et al. 2020). Diversity has also been shown to increase the likelihood of innovation in collaborative processes (Paulus and Nijstad 2003). As SES modeling continues to gain traction as a tool for promoting transdisciplinary co-production processes, we urge modelers not to lose sight of the need for diverse perspectives in the design, evaluation, and application of the model so that they can act as boundary objects, and thereby enable broader participation and understanding.

4.2 Balance power dynamics by incorporating diverse knowledge and data types

While models with diverse participants were more likely to facilitate learning and cooperation, this did not necessarily translate to more diverse types of knowledge populating the models themselves. The knowledge infrastructure that supports SES modeling currently favors quantitative data and modeling approaches over qualitative forms (Elsawah et al. 2019). In fact, there are pervasive epistemological gaps regarding what is even considered "data" across the natural and social sciences, much less how to analyze or validate them (Verburg et al. 2016; Chakraborty et al. 2019). Our results confirm this gap by showing that scientists frequently try to understand SES through the use of pre-existing datasets, the majority of which are biophysical rather than social. By not integrating social data, these models are less likely to reach across multiple social worlds and thus less likely to function as boundary objects. One reason for this might be the perception that qualitative data are exorbitantly expensive in terms of the time and cost of data collection and processing (Alexander et al. 2019; Elsawah et al. 2019). This may reflect a broader SES modeling epistemology that seeks to predict and generalize to other systems rather than engage in expensive and time-consuming processes at local scales that lack transferability to other sites or systems (O'Sullivan et al. 2016). Another reason may be that quantitative data are easier to incorporate into computer-based models. Indeed, we find that quantitative demographic and economic data are the most commonly used social datasets in SES models, while ethnographic, descriptively rich data are incorporated into very few studies. However, it is possible that modelers may be using qualitative data without reporting it in their papers - for example, to conceptualize (rather than parameterize) the model.

There is clear evidence that qualitative data can help place modeling results in a broader context, thus enhancing a models' ability to function as a scalar device. For example, Altaweel et al. (2009) demonstrated that Arctic peoples' decisions about where to source their water impacted their perceptions of system-wide ecological change, which could in turn support or restrict their ability to adapt to climate change in a timely manner. Including qualitative data can also help overcome widely acknowledged shortcomings of SES models, such as the lack of adequate complexity in representing individual decision-making and behavior (Müller et al. 2013; Brown et al. 2013; Preston et al. 2015; Schlüter et al. 2017; Groeneveld et al. 2017) and the ways in which subjective processes associated with human agency and intentionality (i.e., culture and politics) drive the evolution of social rules and positions (Manuel-Navarrete 2015). There is some evidence from our analysis to support this. For example, Rogers et al. (2012) used ethnographic understanding of Mongolian pastoral kinship affinities to demonstrate that weather impacts (both snowstorms and drought) nearly double in severity due to strained social relationships under conditions of restricted movement. Without this detailed understanding of social networks and pressures, their model likely would have underestimated the impact of extreme weather events on the well-being of pastoral communities. Ethnographic and narrative studies of life trajectories can thus help clarify how humans construct their identities and social positions over time, encouraging SES models to move away from purely structural or static rule-based interactions among model agents (Manuel-Navarrete 2015). Qualitative descriptions can also aid in the communication of SES model results, as narratives have been shown to foster greater appreciation of simulation models by non-modelers when compared to aggregated, statistical summaries (Millington et al. 2012).

We also found that models using higher numbers of biophysical datasets were associated with higher system understanding outcomes but lower learning/communication outcomes. For example, Briner et al. (2013) found that biological interdependencies were the most influential factor causing trade-offs between ecosystem services in the Swiss Alps, acknowledging that economic and technological interdependencies were under-represented in their analysis and would benefit from further exploration. They articulated how this improved system understanding could theoretically benefit management and policy, but fell short of describing any clear learning outcomes experienced by practitioners on the ground.

Still, our analysis shows that biophysical datasets are a common and useful tool for understanding cross-scale processes in SES models. Yet, as Callon and Latour (1981) note, scale is not just about moving across space and time - it is also about translation and power. Our review of SES models then raises the question - whose system understanding is being (re)produced by SES models with high biophysical focus? And who is benefitting? An example from Alaska (not included in our model review) illustrates that while participants in a modeling workshop collaborated through engagement with a largely biophysical model, there was a lack of formal avenues for incorporating different observations or data types deemed valuable by local and Indigenous residents into the model (Inman et al. in review). While public participation in the modeling process may have encouraged learning about scientific concepts and collaboration through the model as a boundary object, this would be a unidirectional form of learning as scientists were less likely to incorporate other types of data or knowledge into the model. This unidirectional learning is problematic given the historical tendency for scientists to attempt to validate other forms of knowledge without respecting their unique epistemologies (Agrawal 1995; Nadasdy 1999; Latulippe 2015; Chakraborty et al. 2019). Therefore, SES models that bring diverse people together while still representing only a narrow fraction of the knowledge types involved are not functioning as appropriate technology.

Local ecological knowledge can provide highly detailed understanding to overcome barriers in understanding and representing social processes in SES models. Local knowledge may be particularly useful in data-poor regions around the world, including mountains (Ritzema et al.

2010). For example, Lippe et al. (2011) used qualitative expert knowledge to parameterize a land use model in Northwest Vietnam, enabling a more accurate portrayal of farmers' cropping choices. Moreover, local knowledge itself can act as a scalar device, as knowledge that is transmitted across generations can enhance system understanding across temporal scales (Moller et al. 2004; Gagnon and Berteaux 2009). Though not a modeling study, Klein et al. (2014) found that Tibetan pastoralists who travel further from their home base to higher elevations while herding showed more consensus around climate change and added valuable spatial data beyond what was available from the scant meteorological stations in the region.

It is not yet clear whether more balanced inclusion of social data and local knowledge could resolve the apparent trade-off between system understanding and learning/communication, or whether learning is more dependent on the modeling *process* regardless of the datasets and knowledge types used. It is also not yet clear how to integrate different knowledge types into models without privileging certain ways of knowing. We encourage future research into these questions, and urge modelers to remain cognizant of biases towards disciplinary datasets and of power imbalances in the types of knowledge used and how these might impact participant learning. Studies that examine the kinds of learning experienced by participants are needed to ensure that learning occurs as a mutual and reflexive process among the diverse groups of people involved (Keen et al. 2005; Reed et al. 2010; Fernández-Giménez et al. 2019). Qualitative social science approaches play a powerful role in understanding not just what people want or what they value, but who they are (Callon and Latour 1981), and should therefore be granted a more central role in transdisciplinary SES modeling design and application.

4.3 Promote flexibility in model design

Modelers make a distinction between "complicatedness" and "complexity" in SES models (Sun et al. 2016). When model structures have large numbers of variables or when processes are represented by highly detailed rules and/or equations, these models are said to have high complicatedness (Sun et al. 2016). Meanwhile, model complexity refers to the simulated behaviors that emerge at the system level through application of the model, which can occur even from quite simple models (Conway 1970; Schelling 1971). The aim is for all SES models to mimic some degree of real-world complexity (Balbi and Guipponi 2010). However, modelers still debate how complicated a model needs to be in order to facilitate this emergent complexity and support decision-making outcomes.

Typically, modelers seek the benefits of highly stylized models for testing theories and yielding generalizable results, while highly detailed models are praised for their utility in supporting decision making in complex, real-world situations (Smajgl et al. 2011). Parker et al. (2003) distinguishes between highly stylized simple "Picasso" models and highly detailed empirical "photograph" models, while others describe them as the "KISS: Keep it Simple, Stupid" (Axelrod 1997) versus the "KIDS: Keep it Descriptive, Stupid" approaches (Edmonds and Moss 2004). Some modelers and decision-makers prefer ensemble modeling, integrating multiple diverse models, algorithms, and datasets to produce a single set of recommendations (Elder 2018). In short, there are modelers who believe the more complicated a model is, the better it can be used for decision support and stakeholder learning (Barthel et al. 2008).

Yet, our results do not support these distinctions in disparate benefits from different levels of model complicatedness, and challenge the idea that a model needs to be highly complicated in order to advance societal objectives. Fine-scale SES models in our review were not more likely than coarse-scale models to report greater model purpose outcomes. Furthermore, we found that models that represent processes occurring across multiple scales were not more likely to support higher outcomes than those focusing on processes operating at a single scale. We found no evidence of improved or diminished decision support when higher numbers of modeling approaches were used concurrently in the same study (as in ensemble modeling), or when more datasets were used.

These results further support our assertion that in order to function as appropriate technology in transdisciplinary applications, SES models ought to be designed as boundary objects to address a specific information need presented by a societal problem. We recommend that modelers repeatedly reflect on the needs of their system and diverse end users when considering the scale and choice of modeling approach, rather than assuming finer-scale or highly complicated models will necessarily yield superior results. Viewing these results through the lens of scalar devices, we encourage SES modelers to remain flexible in the ways they represent cross-scalar processes in their models, and to consider in advance how their choice of scale might enable or constrain collaboration among participants - that is, how scale itself functions as a boundary object.

Researchers are still in the early stages of empirically measuring how the design and application of modelling and data visualization tools relate to non-technical stakeholders' capacity to contribute meaningfully to collaborative planning processes (Zellner et al. 2012; Radinsky et al. 2017). There is some indication that models and tools that encourage active, energetic dialogue without overwhelming participants with information (Pelzer et al. 2015) are best suited for these applications. Recent research has shown that participatory modelers often use the modeling approaches they are most familiar with, rather than objectively selecting "the best tools for the job" (Voinov et al. 2018). Our results seem to confirm this, as we do not see any evidence of a particular modeling type or scale yielding higher model purpose outcomes. For example, our analysis demonstrates systems dynamics models usually have high societal orientation, but not necessarily the high learning and decision support outcomes proposed by other reviews (Schlüter et al. 2019). Our finding that decision support outcomes are higher when cellular automata models are not used aligns with previous insights into the limited utility of these approaches for certain contexts (NRC 2014). Yet, nearly half the models in our review were a combination of agent-based models and cellular automata models, highlighting the popularity and flexibility of these particular model types for representing complex SES - something anticipated nearly two decades ago (Parker et al. 2003;

Verburg et al. 2004). Additional empirical studies are needed in the context of SES models for transdisciplinary applications to clarify whether particular modeling approaches or scales can best function as boundary objects.

These findings contribute to ongoing debates about the level of complicatedness needed for SES models to support learning and decision making. Multiple modeling paradigms have emphasized the benefits that emerge from achieving an intermediate level of model complicatedness. Grimm et al. (2005) present this as the "Medawar zone," describing that models are most useful when design is guided by multiple patterns observed at different scales and hierarchical levels. Meanwhile, members of the Companion Modeling network have articulated a "KILT: Keep It a Learning Tool" approach that advocates for slightly less complicated models than the Medawar zone in order to allow diverse stakeholders to connect with the system on their own terms (Le Page and Perrotton 2018). O'Sullivan et al. (2016) have similarly argued that mid-range complicatedness is often the optimal or appropriate level. Yet, our results do not necessarily support these hypotheses in all circumstances. For example, we find that highly context-specific models lead to higher learning outcomes, but this does not necessarily mean finer-scale data or model resolution are required. Meanwhile, decision support seems to be best supported at intermediate (not low or high) levels of generalizability. We encourage more explicit attention to the assessment of participant learning and decision support in future modeling efforts to help resolve these debates and advance our understanding of the role of scale in SES models functioning as appropriate technology.

4.4 Bridge institutional gaps for decision support, learning, and communication

For SES models to act as appropriate technology for transdisciplinary work, they must support decision-making processes and learning for real-world applications. This can be accomplished by ensuring that models act as transdisciplinary boundary objects and facilitate cross-scalar learning as scalar devices. Our review revealed considerable gaps between the intentions and outcomes of

SES models for these purposes. The gap in decision support stemmed from failing to achieve or report outcomes that matched the intended model purpose, while learning/communication outcomes were rarely even intended by most models in our review. While interviews with modelers themselves may help us better understand these gaps, integrating societal goals into model design and application could be one approach to improving transdisciplinary applications of SES models. Yet, this may be difficult for modelers to achieve due to the current knowledge infrastructure surrounding the modeling process. One issue is the stigma sometimes attributed to “applied” research, or the false dichotomy between “applied” and “basic” research that seems to resist simultaneous advances in theoretical and pragmatic fronts (Stokes 1997). Indeed, we did not find any models in our review that supported high scientific as well as high societal orientation - although Brunner et al. (2016a) and Smajgl and Bohensky (2013) came close to achieving this. Both modeling efforts incorporated and explored specific policy interventions while advancing theory and methodologies in the field of SES modeling, indicating a path forward for joint basic and applied research in SES modeling.

Another infrastructural barrier is that some modelers do not appreciate the value of investing time and money in knowledge co-production processes, particularly if their funding mechanisms and career advancement do not reward this kind of engagement with stakeholders. There is some evidence that this is changing, as large-scale funding initiatives such as the Global Challenges Research Fund, the Belmont Forum, and Future Earth require close partnerships between researchers and decision or policy-makers (Mauser et al. 2013; Suni et al. 2016). Researchers also typically operate on slower time scales than societal problems, which may be a source of frustration for communities experiencing severe economic and ecological consequences from global environmental change. These barriers require institutional changes to facilitate and reward modelers’ engagement with societal challenges, and we encourage modelers to begin making incremental changes towards this goal within their own projects and institutions.

5. Conclusions

This study improves our understanding of how SES models can be more appropriately designed and applied to fit transdisciplinary approaches, both in mountains and other SES. First, we found that diversity among the participants involved in modeling can lead to improved collaboration and cooperation for real-world problem solving. As global environmental change increases the need to collaborate across diverse groups for sustainable outcomes in SES, we encourage modelers to take the time to build stronger relationships across academic disciplines and social worlds. Second, we found that diverse participation does not necessarily translate into diverse knowledge and data being incorporated into the model. This suggests that modelers must pay closer attention to issues of power when using SES models as boundary objects, and specifically how diverse perspectives are translated and incorporated into the final model product, or excluded from it. Third, we find that flexibility in model design is a key element for employing SES models as scalar devices in transdisciplinary applications, as the context of the modeling effort is of greater consequence than the technical complicatedness of the model. As STS scholars continue to develop the scalar devices concept into an analytical tool, we encourage more explicit engagement with questions of knowledge translation and power. Finally, we highlight some institutional barriers that may be inhibiting SES modelers from long-term, place-based engagement in societal issues. Creating SES models that are appropriate technology for transdisciplinary applications will require advanced planning, increased funding and attention to the role of diverse data and knowledge, and stronger partnerships across disciplinary divides. Highly contextualized participatory modeling that embraces diversity in both data and actors appears poised to make strong contributions to the world's most pressing environmental challenges.

References

Agrawal, A. 1995. Dismantling the divide between indigenous and scientific knowledge. *Development and Change* 26(3):413-439. https://doi.org/10.1111/j.1467-7660.1995.tb00560.x

Alexander, S.M., Jones, K., Bennett, N.J., Budden, A., Cox, M., Crosas, M., Game, E.T., Geary, J., Hardy, R.D., Johnson, J.T. and Karcher, S., 2019. Qualitative data sharing and synthesis for sustainability science. *Nature Sustainability*, pp.1-8.

Altaweel, M.R., Alessa, L.N. and Kliskey, A.D., 2009. Forecasting Resilience in Arctic Societies: Creating Tools for Assessing Social–Hydrological Systems. *JAWRA Journal of the American Water Resources Association*, *45*(6), pp.1379-1389.

Anselme B, Bousquet F, Lyet A, Etienne M, Fady B, Le Page C. 2010. Modelling of spatial dynamics and biodiversity conservation on Lure mountain (France). Environmental Modelling and Software 25: 1385-1398.

Axelrod, R., 1997. *The complexity of cooperation: Agent-based models of competition and collaboration* (Vol. 3). Princeton University Press.

Balbi, S. and Giupponi, C., 2010. Agent-based modelling of socio-ecosystems: a methodology for the analysis of adaptation to climate change. *International Journal of Agent Technologies and Systems (IJATS)*, *2*(4), pp.17-38.

Balvanera, P., T. M. Daw, T. A. Gardner, B. Martín-López, A. V. Norström, C. Ifejika Speranza, M. Spierenburg, E. M. Bennett, M. Farfan, M. Hamann, J. N. Kittinger, T. Luthe, M. Maass, G. D. Peterson, and G. Perez-Verdin. 2017. Key features for more successful place-based sustainability research on social-ecological systems: a Programme on Ecosystem Change and Society (PECS) perspective. *Ecology and Society* 22(1).

Barnaud C, Bousquet F, Trebuil G. 2008. Multi-agent simulations to explore rules for rural credit in a highland farming community of northern Thailand. Ecological Economics 66: 615-627.

Barnaud, C., C. Le Page, P. Dumrongrojwatthana, and G. Trébuil. 2013. Spatial representations are not neutral: Lessons from a participatory agent-based modelling process in a land-use conflict. Environmental Modelling & Software **45**:150-159.

Barthel R, Janisch S, Schwarz N, Trifkovic A, Nickel D, Schulz C, Mauser W. 2008. An integrated modeling framework for simulating regional-scale actor responses to global change in the water domain. Environmental Modelling and Software 23: 1095-1121.

Bernstein, J. H. 2015. Transdisciplinarity: A Review of Its Origins, Development, and Current Issues:20.

Edwards, P.N., Jackson, S.J., Chalmers, M.K., Bowker, Borgman, C.L., G.C., Ribes, D., Burton, M. and Calvert, S., 2013. Knowledge infrastructures: Intellectual frameworks and research challenges. Report of a workshop sponsored by the National Science Foundation and the Sloan Foundation (Ann Arbor: Deep Blue, 2013), hdl.handle.net/2027.42/97552.

Blumer, H., 1954. What is wrong with social theory?. *American sociological review*, *19*(1), pp.3-10.

Bousquet, F., and C. Le Page. 2004. Multi-agent simulations and ecosystem management: a review. *Ecological Modelling* 176(3):313–332.

Bowker, G.C. and Star, S.L., 1999. *Sorting things out* (Vol. 297). Cambridge, MA: MIT Press.Brandt et al. 2013

Briner, S. H., R; Bebi, P; Elkin, C; Schmatz, DR; and A Grêt-Regamey. 2013. Trade-Offs between Ecosystem Services in a Mountain Region. Ecology and Society **18**.

Brown, D.G., Verburg, P.H., Pontius Jr, R.G. and Lange, M.D., 2013. Opportunities to improve impact, integration, and evaluation of land change models. *Current Opinion in Environmental Sustainability*, *5*(5), pp.452-457.

Brunner, S.H., Huber, R. and Grêt-Regamey, A., 2016. A backcasting approach for matching regional ecosystem services supply and demand. *Environmental Modelling & Software*, *75*, pp.439-458.

Callon, M., & Latour, B. 1981. Unscrewing the big Leviathan: how actors macro-structure reality and how sociologists help them to do so. *Advances in social theory and methodology: Toward an integration of micro-and macro-sociologies*, *1*.

Carlile, P.R., 2002. A pragmatic view of knowledge and boundaries: Boundary objects in new product development. *Organization science*, *13*(4), pp.442-455.

Carpenter, S. R., H. A. Mooney, J. Agard, D. Capistrano, R. S. DeFries, S. Diaz, T. Dietz, A. K. Duraiappah, A. Oteng-Yeboah, H. M. Pereira, C. Perrings, W. V. Reid, J. Sarukhan, R. J. Scholes, and A. Whyte. 2009. Science for managing ecosystem services: beyond the Millennium Ecosystem Assessment. *Proceedings of the National Academy of Sciences* 106(5):1305-1312. https://doi.org/10.1073/pnas.0808772106

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

Cash, D. W., W. C. Clark, F. Alcock, N. M. Dickson, N. Eckley, D. H. Guston, J. Jäger, and R. B. Mitchell. 2003. Knowledge systems for sustainable development. *Proceedings of the National Academy of Sciences* 100(14):8086 -8091. https://doi.org/10.1073/pnas.1231332100

Chakraborty, R., A. S. Daloz, M. Kumar, and A. P. Dimri. 2019. Does Awareness of Climate Change Lead to Worry? Exploring Community Perceptions Through Parallel Analysis in Rural Himalaya. Mountain Research and Development 39 (2). DOI: 10.1659/MRD-JOURNAL-D-19-00012.1

Clark, W.C., Tomich, T.P., Van Noordwijk, M., Guston, D., Catacutan, D., Dickson, N.M., McNie, E., 2011. Boundary work for sustainable development: natural resource management at the consultative group on international agricultural research (CGIAR). Proc. Natl. Acad. Sci. 200900231.

Clarke A and Fujimura J. 1992. *The Right Tools for the Job: At Work in Twentieth-Century Life Sciences*. Princeton University Press.

Clarke, A.E. and Star, S.L., 2008. The social worlds framework: A theory/methods package. *The handbook of science and technology studies*, *3*(0), pp.113-137.

Cohen, A. and Bakker, K., 2014. The eco-scalar fix: Rescaling environmental governance and the politics of ecological boundaries in Alberta, Canada. *Environment and Planning D: Society and Space*, *32*(1), pp.128-146.

Conway, J., 1970. The game of life. Scientific American 223(4) 4.

Crane, T. A. 2010. Of models and meanings: cultural resilience in social–ecological systems. Ecology and Society **15**:19-19.

Cumming, G. S., D. H. M. Cumming, and C. L. Redman. 2006. Scale Mismatches in Social-Ecological Systems: Causes, Consequences, and Solutions. *Ecology and Society* 11(1).

Cundill, G., D. J. Roux, and J. N. Parker. 2015. Nurturing communities of practice for transdisciplinary research. *Ecology and Society* 20(2):art22.

de Laet M and Mol A. 2000. The Zimbabwe Bush Pump: Mechanics of a Fluid Technology *Social Studies of Science* 30(2): 225–263. DOI: 10.1177/030631200030002002.

DeFries, R. S., E. C. Ellis, F. S. Chapin III, P. A. Matson, B. L. Turner II, A. Agrawal, P. J. Crutzen, C. Field, P. Gleick, P. M. Kareiva, E. Lambin, D. Liverman, E. Ostrom, P. A. Sanchez, and J. Syvitski. 2012. Planetary opportunities: a social contract for global change science to contribute to a sustainable future. *BioScience* 62(6):603-606. https://doi.org/10.1525/bio.2012.62.6.11

Dempsey J. 2016. *Enterprising Nature: Economics, Markets, and Finance in Global Biodiversity Politics*. John Wiley & Sons.

Edmonds B., Moss S. 2005. From KISS to KIDS – *An 'Anti-simplistic' Modelling Approach*. In: Davidsson P., Logan B., Takadama K. (eds) Multi-Agent and Multi-Agent-Based Simulation. MABS 2004. Lecture Notes in Computer Science, vol 3415. Springer, Berlin, Heidelberg

Edmonds, B., Le Page, C., Bithell, M., Chattoe-Brown, E., Grimm, V., Meyer, R., Montañola-Sales, C., Ormerod, P., Root, H., Squazzoni, F. 2019. Different Modelling Purposes. Journal of Artificial Societies and Social Simulation 22, 6.

Elder, J. 2018. The Apparent Paradox of Complexity in Ensemble Modeling. In, Nisbet, R., Miner, G., and K. Yale. Handbook of Statistical Analysis and Data Mining Applications. Academic Press. https://doi.org/10.1016/C2012-0-06451-4

Elsawah, S., Filatova, T., Jakeman, A.J., Kettner, A.J., Zellner, M.L., Athanasiadis, I.N., Hamilton, S.H., Axtell, R.L., Brown, D.G., Gilligan, J.M. and Janssen, M.A., 2020. Eight grand challenges in socio-environmental systems modeling. *Socio-Environmental Systems Modelling*, *2*, pp.16226-16226.

Étienne, M. ed., 2013. *Companion modelling: a participatory approach to support sustainable development*. Springer Science & Business Media.

Etienne, M., Du Toit, D. and Pollard, S., 2011. ARDI: a co-construction method for participatory modeling in natural resources management. *Ecology and society*, *16*(1).

Fernández-Giménez, M., D. Augustine, L. Porensky, H. Wilmer, J. Derner, D. Briske, and M. Stewart. 2019. Complexity fosters learning in collaborative adaptive management. *Ecology and Society* 24(2).

Fortun K. 2004. Environmental information systems as appropriate technology. *Design Issues* 20(3): 54–65.Gopalakrishnan, S., and Ganeshkumar, P. 2013. Systematic reviews and meta-analysis: Understanding the best evidence in primary healthcare. *J Family Med Prim Care*. 2(1)9-14.

Fulton, E.A., Smith, A.D., Smith, D.C. and van Putten, I.E., 2011. Human behaviour: the key source of uncertainty in fisheries management. *Fish and fisheries*, *12*(1), pp.2-17.

Gagnon, C. A., and D. Berteaux. 2009. Integrating traditional ecological knowledge and ecological science: a question of scale. *Ecology and Society* 14(2):19. https://doi.org/10.5751/ES-02923-140219

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

Gray, S., Voinov, A., Bommel, P., Le Page, C. and Scmitt-Olabisi, L., 2017. Purpose, processes, partnerships, and products: 4Ps to advance participatory socio-environmental modeling.

Grimm, V. E. Revilla, U. Berger, F. Jeltsch, W.M. Mooij, S.F. Railsback, H.H. Thulke, J. Weiner, T. Wiegand, and D.L. DeAngelis. 2005. Pattern-Oriented Modeling of Agent-Based Complex Systems: Lessons from Ecology. *Science* 310(5750):987–991.

Groeneveld, J., Müller, B., Buchmann, C.M., Dressler, G., Guo, C., Hase, N., Hoffmann, F., John, F., Klassert, C., Lauf, T., Liebelt, V., Nolzen, H., Pannicke, N., Schulze, J., Weise, H., Schwarz, N. (2017) Theoretical foundations of human decision-making in agent-based land use models – A review. Environmental Modelling & Software 87, 39-48.

Harraway, D. 1988. Situated Knowledges: The Science Question in Feminism and the Privilege of Partial Perspective, *Feminist Studies* 14 (3):575-599 (1988)

Hoffmann, S. C. Pohl, and J.G. Hering. 2017. Exploring transdisciplinary integration within a large research program: Empirical lessons from four thematic synthesis processes. *Research Policy*:15.

Hulme M. 2011. Reducing the future to climate: a story of climate determinism and reductionism. *Osiris* 26(1): 245–266.

Inman, S., Esquible, J., Jones, M., Bechtol, B, & Connors, B. In review. Exploring how local data are (and are not) tractable to the management of salmon fisheries. Ecology and Society: State of Alaska's Salmon and People Special Issue.

Jahn, T., M. Bergmann, and F. Keil. 2012. Transdisciplinarity: Between mainstreaming and marginalization. *Ecological Economics* 79:1–10.

Jordan, R., Gray, S., Zellner, M., Glynn, P.D., Voinov, A., Hedelin, B., Sterling, E.J., Leong, K., Olabisi, L.S., Hubacek, K. and Bommel, P., 2018. Twelve questions for the participatory modeling community. *Earth's Future*, *6*(8), pp.1046-1057.

Keen, M., V. A. Brown, and R. Dyball. 2005. *Social learning in environmental management: towards a sustainable future*. Routledge.

Kelly, R.A., Jakeman, A.J., Barreteau, O., Borsuk, M.E., ElSawah, S., Hamilton, S.H., Henriksen, H.J., Kuikka, S., Maier, H.R., Rizzoli, A.E. and Van Delden, H., 2013. Selecting among five common modelling approaches for integrated environmental assessment and management. *Environmental modelling & software*, *47*, pp.159-181.

Klein, J. A., K. A. Hopping, E. T. Yeh, Y. Nyima, R. B. Boone, and K. A. Galvin. 2014. Unexpected climate impacts on the Tibetan Plateau: local and scientific knowledge in findings of delayed summer. *Global Environmental Change* 28:141-152. https://doi.org/10.1016/j.gloenvcha.2014.03.007

Klein, J.A., Tucker, C.M., Nolin, A.W., Hopping, K.A., Reid, R.S., Steger, C., Grêt-Regamey, A., Lavorel, S., Müller, B., Yeh, E.T. Boone, R.B., Bourgeron, V., Bustic, V., Castellanos, E., Chen, X., Dong, S.K., Greenwood, G., Keiler, M., Marchant, R., Seidl, R., Spies, T., Thorn, J., Yager, K., and the Mountain Sentinels Collaborative Network. 2019. Catalyzing transformations to sustainability in the world's mountains. *Earth's Future*, *7*(5), pp.547-557.

Lade, S.J., Haider, L.J., Engström, G. and Schlüter, M., 2017. Resilience offers escape from trapped thinking on poverty alleviation. *Science Advances*, *3*(5), p.e1603043.

Lambin, E. F., and P. Meyfroidt. 2010. Land use transitions: socio-ecological feedback versus socio-economic change. *Land Use Policy* 27(2):108-118. https://doi.org/10.1016/j.landusepol.2009.09.003

Lambin, E. F., B. L. Turner, H. J. Geist, S. B. Agbola, A. Angelsen, J. W. Bruce, O. T. Coomes, R. Dirzo, G. Fischer, C. Folke, P. S. George, K. Homewood, J. Imbernon, R. Leemans, X. Li, E. F. Moran, M. Mortimore, P. S. Ramakrishnan, J. F. Richards, H. Skånes, W. Steffen, G. D. Stone, U. Svedin, T. A. Veldkamp, C. Vogel, and J. Xu. 2001. The causes of land-use and land-cover change: moving beyond the myths. *Global Environmental Change* 11(4):261-269. https://doi.org/10.1016/S0959-3780(01)00007-3

Landström C, Whatmore SJ, and SN Lane. 2011. Virtual Engineering: Computer Simulation Modelling for Flood Risk Management in England. *Science Studies*: 20.

Lang, D. J., A. Wiek, M. Bergmann, M. Stauffacher, P. Martens, P. Moll, M. Swilling, and C. J. Thomas. 2012. Transdisciplinary research in sustainability science: practice, principles, and challenges. *Sustainability Science* 7(S1):25–43.

Latour, B. 1986*. Laboratory life: The Construction of Scientific Facts.* Princeton, N.J. :Princeton University Press.

Latulippe, N. 2015. Situating the work: a typology of traditional knowledge literature. *AlterNative: An International Journal of Indigenous Peoples* 11(2):118-131. https://doi.org/10.1177/117718011501100203

Le Page, C., and A. Perrotton. 2018. KILT: A Modelling Approach Based on Participatory Agent-Based Simulation of Stylized Socio-Ecosystems to Stimulate Social Learning with Local Stakeholders. Pages 156–169 *in* G. P. Dimuro and L. Antunes, editors. *Multi-Agent Based Simulation XVIII*. Springer International Publishing, Cham.

Lemos, M.C., Arnott, J.C., Ardoin, N.M., Baja, K., Bednarek, A.T., Dewulf, A., Fieseler, C., Goodrich, K.A., Jagannathan, K., Klenk, N. and Mach, K.J. 2018. To co-produce or not to co-produce. *Nature Sustainability*, *1*(12), pp.722-724.

Letcher RA, Croke BFW, Jakemann AJ, Merritt WS. 2006a. An integral modeling toolbox for water resources assessment and management in highland catchments: Model description. Agricultural Systems 89: 106-131.

Levi-Strauss, C. 1962. Totemism. Translated by Rodney Needham. Merlin Press: London.

Lippe M, Min TT, Neef A, Hilger T, Hoffmann V, Lam NT, Cadisch G. 2011. Building on qualitative datasets and participatory processes to simulate land use change in a mountain watershed of Northwest Vietnam. Environmental Modelling and Software 26: 1454-1466.

Lippe, M., Bithell, M., Gotts, N., Natalini, D., Barbrook-Johnson, P., Giupponi, C., Hallier, M., Hofstede, G.J., Le Page, C., B. Matthews, R., Schlüter, M., Smith, P., Teglio, A., Thellmann, K. 2019. Using agent-based modelling to simulate social-ecological systems across scales. GeoInformatica 23, 269–298.

Liu, J., T. Dietz, S. R. Carpenter, M. Alberti, C. Folke, E. Moran, A. N. Pell, P. Deadman, T. Kratz, and J. Lubchenco. 2007. Complexity of coupled human and natural systems. *science* 317(5844):1513–1516.

Mahony M. 2014. The predictive state: Science, territory and the future of the Indian climate. *Social Studies of Science* 44(1): 109–133. DOI: 10.1177/0306312713501407.

Mauser, W., G. Klepper, M. Rice, B. S. Schmalzbauer, H. Hackmann, R. Leemans, and H. Moore. 2013. Transdisciplinary global change research: the co-creation of knowledge for sustainability. *Current Opinion in Environmental Sustainability* 5(3–4):420–431.

Millington, J.D., O'Sullivan, D. and Perry, G.L., 2012. Model histories: Narrative explanation in generative simulation modelling. *Geoforum*, *43*(6), pp.1025-1034.

Moller, H., F. Berkes, P. O. Lyver, and M. Kislalioglu. 2004. Combining science and traditional ecological knowledge: monitoring populations for co-management. *Ecology and Society* 9(3):2. https://doi.org/10.5751/ES-00675-090302

Müller, B., Bohn, F., Dreßler, G., Groeneveld, J., Klassert, C., Martin, R., Schlüter, M., Schulze, J., Weise, H., Schwarz, N., 2013. Describing human decisions in agent-based models–ODD+ D, an extension of the ODD protocol. Environmental Modelling & Software 48 37-48.

Nadasdy, P. 1999. The politics of TEK: power and the "integration" of knowledge. *Arctic Anthropology* 36(1/2):1-18.

National Research Council. 2014. Advancing Land Change Modeling: Opportunities and Research Requirements. Board on Earth Sciences and Resources, National Academies Press: Washington, D.C., 152 pp.

Norström, A.V., Cvitanovic, C., Löf, M.F., West, S., Wyborn, C., Balvanera, P., Bednarek, A.T., Bennett, E.M., Biggs, R., de Bremond, A. and Campbell, B.M., 2020. Principles for knowledge co-production in sustainability research. *Nature sustainability*, pp.1-9.

Nost E. 2019. Climate services for whom? The political economics of contextualizing climate data in Louisiana's coastal Master Plan. *Climatic Change*. DOI: 10.1007/s10584-019-02383-z.

O'Lear S. 2016. Climate science and slow violence: A view from political geography and STS on mobilizing technoscientific ontologies of climate change. *Political Geography* 52: 4–13. DOI: 10.1016/j.polgeo.2015.01.004.

O'Sullivan D. 2004. Complexity science and human geography. *Transactions of the Institute of British Geographers* 29(3): 282–295.

O'Sullivan, D., Evans, T., Manson, S., Metcalf, S., Ligmann-Zielinska, A. and Bone, C., 2016. Strategic directions for agent-based modeling: avoiding the YAAWN syndrome. *Journal of land use science*, *11*(2), pp.177-187.

Ostrom, E. 2007. A diagnostic approach for going beyond panaceas. *Proceedings of the national Academy of Sciences* 104(39):15181-15187. https://doi.org/10.1073/pnas.0702288104

Parker, D.C., Manson, S.M., Janssen, M.A., Hoffmann, M.J. and Deadman, P., 2003. Multi-agent systems for the simulation of land-use and land-cover change: a review. *Annals of the association of American Geographers*, *93*(2), pp.314-337.

Paulus, P. B., and B. A. Nijstad. 2003. *Group creativity: Innovation through collaboration*. Oxford University Press.

Pelzer, Peter, Gustavo Arciniegas, Stan Geertman, and Sander Lenferink. 2015. "Planning Support Systems and Task-Technology Fit: A Comparative Case Study." Applied Spatial Analysis and Policy 8 (2), 155–175. doi:10.1007/s12061-015-9135-5.

Polasky, S., S. R. Carpenter, C. Folke, and B. Keeler. 2011. Decision-making under great uncertainty: environmental management in an era of global change. *Trends in Ecology & Evolution* 26(8):398–404.

Preston, B.L., King, A.W., Ernst, K.M., Absar, S.M., Nair, S.S. and Parish, E.S., 2015. Scale and the representation of human agency in the modeling of agroecosystems. *Current Opinion in Environmental Sustainability*, *14*, pp.239-249.

Radinsky, J., Milz, D., Zellner, M., Pudlock, K., Witek, C., Hoch, C. and Lyons, L., 2017. How planners and stakeholders learn with visualization tools: using learning sciences methods to examine planning processes. *Journal of Environmental Planning and Management*, *60*(7), pp.1296-1323.

Rammer, W., and R. Seidl. 2015. Coupling human and natural systems: Simulating adaptive management agents in dynamically changing forest landscapes. Global Environmental Change **35**:475-485.

Rayner S, Lach D and Ingram H. 2005. Weather forecasts are for wimps: why water resource managers do not use climate forecasts. *Climatic Change* 69(2): 197–227.

Reed, M., A. C. Evely, G. Cundill, I. R. A. Fazey, J. Glass, A. Laing, J. Newig, B. Parrish, C. Prell, and C. Raymond. 2010. What is social learning? *Ecology and society*.

Ribes, D. and Finholt, T.A. 2008. November. Representing community: knowing users in the face of changing constituencies. In *Proceedings of the 2008 ACM conference on Computer supported cooperative work* (pp. 107-116).

Ribes, D. 2014. February. Ethnography of scaling, or, how to a fit a national research infrastructure in the room. In *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing* (pp. 158-170).

Ritzema, H., Froebrich, J., Raju, R., Sreenivas, C., Kselik, R., 2010. Using participatory modelling to compensate for data scarcity in environmental planning: a case study from India. Environmental Modelling and Software 25 (11), 1267e1488.

Rogers, J.D., Nichols, T., Emmerich, T., Latek, M., Cioffi-Revilla, C. 2012. Modeling scale and variability in human–environmental interactions in Inner Asia. Ecological Modelling, 241, 5-14, ISSN 0304-3800, http://dx.doi.org/10.1016/j.ecolmodel.2011.11.025.

Schelling, T.C., 1971. Dynamic models of segregation†. Journal of mathematical sociology 1(2) 143-186.

Schlüter, M., Baeza, A., Dressler, G., Frank, K., Groeneveld, J., Jager, W., Janssen, M.A., McAllister, R.R., Müller, B., Orach, K. and Schwarz, N., 2017. A framework for mapping and comparing behavioural theories in models of social-ecological systems. *Ecological Economics*, *131*, pp.21-35.

Schlüter, M., Müller, B., Frank, K. 2019. The potential of models and modeling for social-ecological systems research: the reference frame ModSES. Ecology and Society 24.

Smajgl, A., and E. Bohensky. 2013. Behaviour and space in agent-based modelling: Poverty patterns in East Kalimantan, Indonesia. Environmental Modelling & Software **45**:8-14.

Smajgl, A., Brown, D.G., Valbuena, D. and Huigen, M.G., 2011. Empirical characterisation of agent behaviours in socio-ecological systems. *Environmental Modelling & Software*, *26*(7), pp.837-844.

Star, S.L., Griesemer, J.R., 1989. Institutional ecology,translations' and boundary objects: amateurs and professionals in Berkeley's museum of vertebrate zoology, 1907–39. Soc. Stud. Sci. 19, 387–420.

Steger, C., Nigussie, G., Alonzo, M., Warkineh, B., Van Den Hoek, J., Fekadu, M., Evangelista, P. and Klein, J., 2020. Knowledge coproduction improves understanding of environmental change in the Ethiopian highlands. *Ecology and Society*, *25*(2).

Steger, C., S. Hirsch, C. Evers, B. Branoff, M. Petrova, M. Nielsen-Pincus, C. Wardropper, and C. J. Van Riper. 2018. Ecosystem services as boundary objects for transdisciplinary collaboration. *Ecological Economics* 143:153-160. https://doi.org/10.1016/j.ecolecon.2017.07.016

Stokes, DE. 1997. Pasteur's Quadrant – Basic Science and Technological Innovation. Brookings Institution Press. pp. 196

Sun, Z., Lorscheid, I., Millington, J.D., Lauf, S., Magliocca, N.R., Groeneveld, J., Balbi, S., Nolzen, H., Müller, B., Schulze, J. and Buchmann, C.M., 2016. Simple or complicated agent-based models? A complicated issue. *Environmental Modelling & Software*, *86*, pp.56-67.

Sundberg M. (2010) Organizing Simulation Code Collectives. *Science Studies*: 21.

Suni, T., S. Juhola, K. Korhonen-Kurki, J. Käyhkö, K. Soini, and M. Kulmala. 2016. National Future Earth platforms as boundary organizations contributing to solutions-oriented global change research. *Current opinion in environmental sustainability* 23:63–68.

Taylor, P.J., 2005. *Unruly complexity: Ecology, interpretation, engagement*. University of Chicago Press.

Tengö, M., E. S. Brondizio, T. Elmqvist, P. Malmer, and M. Spierenburg. 2014. Connecting diverse knowledge systems for enhanced ecosystem governance: the multiple evidence base approach. *Ambio* 43(5):579-591. https://doi.org/10.1007/s13280-014-0501-3

Thorn, J.P.R., Steger, C., Hopping, K., Capitani, C., Marchant, R., Tucker, C., Nolin, A., Reid, R., Seidl, R., Chitale, and Klein, J. In review. A systematic review of participatory scenario planning to envision mountain social-ecological systems futures. *Ecology and Society.*

Turner, B. L., E. F. Lambin, and A. Reenberg. 2007. The emergence of land change science for global environmental change and sustainability. *Proceedings of the National Academy of Sciences* 104(52):20666-20671. https://doi.org/10.1073/pnas.0704119104

Verburg, P. H., J. A. Dearing, J. G. Dyke, S. van der Leeuw, S. Seitzinger, W. Steffen, and J. Syvitski. 2016. Methods and approaches to modelling the Anthropocene. *Global Environmental Change* 39:328–340.

Verburg, P.H., Schot, P.P., Dijst, M.J. and Veldkamp, A., 2004. Land use change modelling: current practice and research priorities. GeoJournal, 61(4), pp.309-324.

Voinov, A., and F. Bousquet. 2010. Modelling with stakeholders. Environmental Modelling and Software 25:1268–1281.

Voinov, A., Jenni, K., Gray, S., Kolagani, N., Glynn, P.D., Bommel, P., Prell, C., Zellner, M., Paolisso, M., Jordan, R. and Sterling, E., 2018. Tools and methods in participatory modeling: Selecting the right tool for the job. *Environmental Modelling & Software*, *109*, pp.232-255.

Walker, B., Holling, C.S., Carpenter, S.R. and Kinzig, A., 2004. Resilience, adaptability and transformability in social–ecological systems. *Ecology and society*, *9*(2).

Wyborn, C., Datta, A., Montana, J., Ryan, M., Leith, P., Chaffin, B., Miller, C. and Van Kerkhoff, L., 2019. Co-producing sustainability: Reordering the governance of science, policy, and practice. *Annual Review of Environment and Resources*, *44*, pp.319-346.

Zellner, M. L., L. B. Lyons, C. J. Hoch, J. Weizeorick, C. Kunda, and D. C. Milz. 2012. “Modeling, Learning, and Planning Together: An Application of Participatory Agent-Based Modeling to Environmental Planning.” URISA Journal 24 (1): 77–93.

Zellner, M.L., 2008. Embracing complexity and uncertainty: the potential of agent-based modeling for environmental planning and policy. *Planning theory & practice*, *9*(4), pp.437-457.

Zimmerer, K.S. and Bassett, T.J. eds., 2003. *Political ecology: an integrative approach to geography and environment-development studies*. Guilford Press.