Reflections on SES modeling: Stop me if you've heard this

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Abstract

Key lessons about and limits to social-ecological systems (SES) modeling are widely available and frustratingly consistent over time. Prominent challenges include outdated perspectives about systems and models along with persistent disciplinary hegemony. The inherent complexity in SES means that an emphasis on discrete prediction is misplaced and has potentially reduced model efficacy for decision-making. Although computer models are definitely the tool to use to identify the complex relationships within SES, humans are messy and hence the 'social' in SES is often ignored, glossed over, or reduced to simplistic economic or demographic variables. This combination of factors has perpetuated biases in what is worth pursuing and/or publishing.

In (re)visiting issues in SES modeling, including debates about model capabilities, data selection, and challenges in working across disciplinary lines, this reflection explores how the author's experience aligns with extant literature as well as raises issues about what is absent from that body of work. The available lessons suggest that scholars and practitioners need to re-think how, why, and when to employ SES modeling in regulatory or other decision-making contexts.

Keywords

Social-ecological systems; modeling, boundary object; interdisciplinary; decision-making

1. Background

Disclosure—much of the following content is not new. Most of my observations about social-ecological systems (SES) modeling are widely reported in the extant literature. In fact, they border on the repetitive. This state of affairs is precisely what prompted me to prepare this reflection. *The sobering reality is that despite years dedicated to improving decision-making via SES models, commentary on the challenges and limitations remains remarkably consistent.* This reflection (re)visits issues in SES modeling, including debates about what models can and can't do, data selection and use, challenges in working across disciplinary lines, as well as biases in what garners attention. In this paper I explore my own experience as it largely aligns with contemporary literature, but also as it offers insight into what is not well-documented. The lessons I, and others, have learned point to ways forward that may better utilize SES modeling capabilities.

Early in my professional career I was ambivalent about computer models. I worried about bias in what models could actually represent within social and ecological systems. But as my thinking shifted from the 'balance of nature' fallacy to a dynamic system reality, and as I learned more about limits of human cognition, it became abundantly clear that computer models are necessary to better understand SES. I was heavily influenced by

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Botkin's (1990) conclusion that models help us avoid a dichotomous view of nature as always constant or never constant and the idea that "models help us synthesize what is too complex for our minds to combine working alone" (p. 120). Likewise, I was convinced by Lee's (1993) observations that engaging with ecological complexity requires models because without them, "human misunderstanding persists, unaware of its errors" (p. 62). I subsequently embraced computer modeling and like many converts, became a devoted proselytizer to employing models as a path toward better decisions for adapting to or managing SES.

I learned about integrative modeling from modelers who recognized the oft quoted idea that, ''all models are wrong; but some are useful'' (usually attributed to statistician George Box). These modelers used system dynamics approaches, which support Lindblom's (1979) idea that all analyses are incomplete, but analyses designed with that incompleteness in mind are better than analyses with random incompleteness. To that end, I brought social science and humanities perspectives to a variety of multi-year SES modeling projects, mostly focused on water management in the US southwest. These were all collaborative efforts and team composition ranged from only researchers to extensive public engagement in model development. Each project was designed to try to capture the complexity within relevant SES and the teams hoped the models would be used in decision-making. In two cases, state-mandated decision-making processes catalyzed the modeling project. As this reflection will further discuss, none of the models offered equivalent levels of complexity in considering social and physical systems and their influence in supporting decision-making is mixed.

Although it has been a decade since I worked on a modeling team, I have kept an eye open for publications about SES modeling and as already noted, have found these reports quite repetitive. Many of the issues that were present 20 years ago remain. Therefore, while I continue to support models as instrumental to improving how we manage and adapt to SES, experience and time have gentled my passion for them.

2. Approach

My intention here is to think about SES modeling writ large. I am not assessing or comparing kinds of models and am agnostic as to any particular topic within the SES milieu. Rather, I am reflecting on my own experiences. Because memory is fallible, I did review notes and official reports, as well as peer reviews and published papers from all of the modeling projects I have worked on.

This is a reflection and not a comprehensive literature review. However, I do utilize a review of reviews approach. To ensure I had recent information, in January 2023 I searched Google Scholar for "social ecological systems" AND model* AND review; NOT conceptual, mental, framework from 2020-2023. This returned more than 1700 items and I skimmed all of the titles and found several literature reviews I had not previously read. These recent reviews coupled with older reviews represent hundreds of articles published over 20 years and covering various modeling approaches (e.g. agent-based modeling, collaborative modeling). This provides a strong basis for the observations made here about what has persisted in the SES modeling milieu over time.

3. Gleanings

The following sections highlight debates about what models are capable of as well as disconnects in stated intentions and the reality of model development and implementation. Commonly stated intentions for developing SES models are to understand the system(s), to make predictions, and to contribute to decision-making. There remains, however, a consistent lack of attention to the 'social' in SES, which limits model applicability. Additionally, and perhaps most importantly, there are multiple layers of bias exhibited in SES model development processes as well as in what information is disseminated about those processes and about model output.

3.1 Model Intent and Capability

My experiences confirm Botkin's (1990) observation that people tend to either believe in computer models "too much or too little." In modeling projects that engaged the public, I encountered people in the 'too much' camp, who feared that a 'black box' was replacing human agency in decision-making. In the 'too little' camp, there were participants in each project who hoped or expected that the model would provide definitive predictions and concomitant solutions to the issue at hand. Yet, like most SES management issues, these projects were embedded in "wicked problems" which defy precise prediction or singular solution (Rittel and Webber, 1973). Indeed, "The contingent nature of human behaviour severely limits the potential for testable, quantitative predictions in social-ecological systems" (Rounsevell et al., 2014, p. 130). Connecting the 'too much' and 'too little' perspectives, decision-makers often prefer predictive models because "model results provide a decision-making crutch: models can make decisions for decision-makers" (Allison et al. 2018, p. 149). Policy-makers struggle to accept the complexity of wicked problems and seek simple solutions, so a 'black box' is palatable. My experiences revealed that the general public can express fear of a 'black box' while simultaneously expecting that a model can and should provide predictions that reveal solutions. Given this context, it is not surprising that prediction remains an explicitly stated focal point for many SES modeling efforts (Drechsler, 2020; Steger et al., 2021).

Intense discussions about what models can or should do within a particular context, including if they could predict, were common in all the modeling teams I joined, even where all collaborators were researchers. These discussions were more complicated and often more contentious in projects that included decision-makers and/or the public. There were often various views expressed on what was meant by 'predict' and to what end prediction was desired or necessary. More specifically, these discussions routinely focused on whether model output would be useful in a decision context. The modelers I worked with often stressed that the models being developed were best suited to showing trends or perhaps relative scale for particular phenomena, and were less adept at providing precise, numeric prediction. Yet, there was at least one person in each project who at some point in the process insisted that without definitive, predictive capability the model would be useless in any decision-making context. This prevailing emphasis on prediction, which is a proxy for certainty, reflects an historic artifact of the mechanistic, 'balanced' view of the world in which linear models of some physical systems can offer stable, definitive predictions (Cockerill et al., 2009; Cockerill, 2010; Schlüter et al., 2012). This view, however, is quite off the mark for addressing integrated social and ecological systems, which are by definition highly uncertain and therefore not highly predictable.

3.2 Modeling the Social

Discussions about model intent and capability often revealed a tendency for individuals to believe (or perhaps wish) that more or better information would convince people of various 'truths' and this would subsequently change perceptions, attitudes, and behavior. I once noted in a modeling team meeting that no model could be a 'silver bullet' for decision-making. One of the natural scientists asked why not, because from his perspective, the collaboratively-developed model would show the 'reality' of what was happening and that would convince people to take appropriate actions. This view belies the preponderance of evidence from research in human cognition, group dynamics, and other fields that rejects the simplistic 'deficit model' whereby providing relevant, accurate information will alter attitudes or behavior. As Hellstrom and Jacob (1996) noted decades ago, "In practice, most environmental negotiation processes are not about facts per se, but about whose value judgments are to be represented in making decisions" (p. 80). Subsequently, "modeling is essentially a mediation process" (Mollinga, 2010, p. S-5). This is why who develops a model strongly influences whether people will trust that model (Cockerill et al., 2004). Indeed, in my experience, when model results did not replicate preconceived ideas, members of the public and some decision-makers concluded that the model was wrong rather than question their understanding of the system(s). Thus, even though models are necessary to reveal complex SES relationships, those results may not resonate with potential model users and hence may not affect any decision.

While scholars have long recognized that how humans make any decision to act is much more complicated than simply receiving information, figuring out how to capture data about what people think, feel, believe or value in any given context is immensely difficult. Integrating diverse social data with ecological data into a computer model presents an even larger challenge and remains the exception in SES modeling. I have had the good fortune to work with modelers who fully embrace thinking broadly about how to capture relationships across these systems. Nonetheless, despite the best of intentions, in practice the teams tended to model physical aspects first and then thought about how social data might align. The initial social purview for these modeling teams was relatively broad, but eventually narrowed to simple demographics and/or a limited economic focus. This reflected various levels of debate among disciplines represented on the modeling teams. As the final report from one project noted, "The quantitative scientists were focused to the end on making the model work as a measure of project success" (McNamara et al., 2004) and employing economic data was simpler than dealing with the messy qualitative data that the social scientists were considering. In other projects some team members resisted using any qualitative data or even accepting any non-economic expertise or data. Although relying on quantifiable data was expedient for finalizing projects and potentially increased publishing opportunities, it reduced the complexity in what was being modeled. While colleagues and I document debates about data selection for these models (Cockerill et al., 2007; Cockerill et al., 2010) the published texts do not emphasize the limitations that this placed on model complexity and any subsequent relevance to decision-making.

Disciplinary differences and decreasing model complexity were definitely not unique to my modeling teams. The difficulties of working across disciplinary and methodological lines feature prominently in the “grand challenges” to SES modeling that Elsawah et al. (2020) describe. *As a result, the reviews cited in this paper are unanimous in concluding that the ‘social’ in SES is seriously under-represented in models.* Interestingly, even though many models are intentionally designed to influence public policy or government decision-making, more than a third of those featured in one review did not integrate any aspect of governance (Bourceret et al., 2021). Further, across all model topics, the reviews recognize that what is included under the social moniker is typically narrowly focused economic theory and/or data. To wit, agent-based models for flood risk emphasize rational actors and cost-benefit analysis (Taberna et al., 2020) while integrated watershed modeling most commonly employs cost-benefit analysis to represent social conditions (Cooper, 2015). Likewise, economic factors were by far the most common “human dimension” variables included in fisheries models (Weber et al., 2019) and forestry models largely exclude non-market factors (Riviere et al., 2020). Economics derived data (e.g. price, cost, income) and neo-classic, rational actor, utility based economic theories dominate most SES models (Groeneveld et al., 2017; Drechsler, 2020; Solomon et al., 2020; Bourceret et al., 2021). Yet, there is increasing evidence that *Homo economicus* does not represent actual people and the way they think or act (Schill et al., 2019). Moreover, many modelers claim that their intended purpose is to understand the system(s) being modeled (Groenveld et al., 2017; Drechsler, 2020; Steger et al., 2021) yet they clearly take a myopic view of the relevant system(s).

The modelers I worked with fully recognized that limiting the scope raised concerns for how well a model could capture actual system dynamics. Likewise, all of the reviews I cite recognize that the limited ‘social’ in SES modeling is a problem and most offer potential opportunities for capturing a broader array of social dynamics. One commonly identified difficulty that echoes my experience, is finding ways to align social data with ecologic data. Because empirical knowledge about human decision-making is “fragmented, context dependent and descriptive” it resists being transformed into “crisp causal relationships” (Schlüter et al., 2017, p. 23) that many SES models seek. The recent evidence of a limited application of social information suggests that little has changed since Vallury et al. (2022) found that in empirical research focused on SES, projects that used simulation models rarely employed focus group, interview, or survey data. The system dynamics approach that my teams used does allow mental models to be encoded into the computer model, so users can explore relationships even where numeric data are weak (Sterman, 2000). This method was often resisted, however, due to disciplinary hegemony. Subsequently, the modelers defaulted to more readily quantifiable data, especially if there was pressure for the model to provide some level of prediction or pressure to wrap up the project.

3.3 Model Lessons and Missing Models

One of the most salient lessons I’ve learned from engaging in SES modeling projects and reviewing the literature is that it can be a struggle to learn from previous efforts. An initial challenge is the sheer amount of available information. As noted, the reviews cited here reflect hundreds of papers focused on various aspects of SES modeling across diverse topics as well as a proliferation of specific models employed (see Schulze et al., 2017). Beyond model-focused work, Colding and Barthel (2019) document that the SES concept has diffused across a broad array of subject areas to include accounting, the arts, and medicine. This diaspora encompasses a plethora of definitions for SES. Further, there remains a dearth of attention to comparative studies or synthetic analyses beyond the literature reviews about SES modeling (Elsawah et al., 2020). This is in part due to the “methodological pluralism” that characterizes SES work generally and hampers effective synthesis (Vos et al., 2019). Of course, comparing models or synthesizing across projects may be a moot point if the models insist on being predictive and/or have a narrow social focus and hence a limited perspective on SES complexity.

Specific to decision-making, it is a challenge to learn about model use in decisions because that information is often not reported. Steger et al. (2021) found that about 38% of the models reviewed that had a stated intent to inform decision-making did not report any decision-making outcomes. This perhaps reflects that those models were not used as the modelers had planned or hoped. I sympathize. As already noted, all of the modeling projects I worked on hoped to have the models used in decision-making. Several were not used in any decision-making capacity for a variety of reasons, including lack of a champion with decision-making authority and generating results that did not support pre-existing ideas or prevailing policy. One project was caught up in contentious political debates that included competing models and the final project report concluded, “it has been difficult to gage the acceptance level from the stakeholders” (Sun et al., 2012, p.3). One model was used in public fora to generate scenarios that did influence a water management plan. The model, however, was not recognized in the plan itself (Cockerill et al., 2006). Publications about these projects tend to gloss over reasons why they were not more central to decisions being made.

This raises perhaps the most significant issue facing SES modeling: the various layers of bias in what information is generated and communicated as well as where it is communicated. At a very basic level, there are likely SES modeling projects where the participants have no need or incentive to publish. In other cases, project sponsors can restrict publishing if they fear reactions to the model or its results. This is tied to long-standing bias toward only publishing ‘successes’ and limited interpretations of what qualifies as a success. Peer reviews on my manuscripts about modeling projects often explicitly emphasized that the work needed to highlight success to make it relevant. The definition of success was, in several cases, limited to showing strong validation for model output and/or evidence of model performance in making some decision. Such reviews encourage authors to ‘sugar coat’ negatives and overemphasize positive aspects of projects that had mixed results, even when negative results may be more instructional. In fact, Steger et al. (2021) found considerable differences between the stated intentions among various SES modeling projects and the reported outcomes from those projects. Many projects they reviewed did not report outcomes at all for one or more stated intentions, suggesting weak attention to detail in writing and editing or that those outcomes were not perceived as positive and hence not included.

Because they are absent in the literature, it is impossible to know if negative results show problems with how well a model functioned or if the model development process was weak or both. This bias remains as relevant today as it did two decades ago, when Rouwette and colleagues (2002) lamented that the literature on collaborative modeling did not reflect efforts that failed to reach their goals or suffered from poor group dynamics. Specific to model development processes, while public participation is widely perceived as desirable or even necessary for SES relevant decision-making, the pitfalls or unintended consequences from broadly collaborative modeling efforts remain under-examined (but do see Cockerill et al., 2009; Lim et al., 2023). Regarding my work, peer reviewers sometimes criticized manuscripts that focused on model development processes because they did not focus more on the nuts and bolts of the model itself. In the broader body of literature, Voinov et al. (2016) affirmed that assessing model development processes was relatively rare.

SES modeling articles are found predominantly in ecology, modeling, and engineering journals (Groenveld et al., 2017; Bourceret et al., 2021). Given the volume of material published, there is undoubtedly a tendency to remain siloed and to be well-versed in the literature within a particular field, but largely ignorant of relevant work in other fields. This is true even within modeling itself, as Gray et al. (2018) note that work with system dynamics models and work with agent-based models tend to be published in different venues. To be sure, when preparing our own proposals and publications, colleagues and I relied heavily on the most similar previous work. While I recognize that no review is complete, my perusal of the literature reveals that authors do not always cite articles that I know exist and are relevant.

In addition to modeling teams being isolated, Elsawah et al. (2020) note that funders and publishers also remain fixed in disciplinary silos, so projects that are interdisciplinary and integrative struggle to find financial support and publishing outlets. As an interdisciplinary scholar, I am accustomed to receiving widely disparate reviews on manuscripts submitted for publication. This was definitely true for the various SES modeling projects I helped document. On multiple occasions my co-authors and I received a ‘reject’ and a ‘publish as is’ review for the same manuscript. Multiple negative review comments focused on the methods employed because they did not align neatly with the reviewer’s expected disciplinary method and in one case a reviewer chastised us because the model did not produce clear predictions.

These various biases definitely resulted in some of our work never being published and affected where and when other work was published, which has subsequently influenced if or when that work is cited. I doubt my colleagues and I are alone in experiencing this. Hence, despite the volumes published about SES modeling, the body of work is skewed. The lack of widely available counterfactual information potentially means that modeling groups are working in echo chambers that continue to promote theories, methods and data types that are not productive. This, coupled with publishing biases means that many potential lessons learned are not available so SES modeling has not advanced as far or as rapidly as it might have.

4. Future Modeling

As Botkin (1990), Lee (1993) and others recognized long ago, models are necessary to understand SES systems and reviews do show that understanding a system is a common purpose for SES model development, (Groeneveld et al., 2017; Drechsler, 2020; Steger et al., 2021). This makes intuitive sense given the concomitant emphasis on prediction and decision-making. These multiple intents, however, also continue to rely on flawed assumptions and historic mechanistic views. While recognizing that SES are too complex for human brains to grasp, there is a simultaneous assumption that prediction is possible and this drives the propensity to limit 'social' inputs to data that seems quantifiable. There is also an inherent 'deficit model' approach which suggests that if the model accurately reflects the system (a significant "if") and predicts something, this will clarify what to decide. Because SES are complex and modeling is often addressing wicked problems, emphasizing discrete prediction is misplaced, even if that is what a decision-maker or the public seek. Additionally, as already noted, simply providing evidence about how SES functions may or may not influence decisions.

To upend the repetitive nature of lessons reported about SES modeling, future practitioners should embrace a broader disciplinary perspective while simultaneously narrowing expectations for models in decision-making settings. Adaptation and resilience - common tropes in SES work - emphasize and accept complexity, uncertainty and an ability to learn. Yet, many SES modeling efforts continue to reduce complexity and attempt to reduce uncertainty rather than seeking ways to cope with uncertainty and to learn how to adapt as new situations arise (see Schlüter et al., 2012, 2019; Elsawah et al., 2020; Rounsevell et al., 2021). As noted in a special issue of American Scientist dedicated to re-thinking how best to use models, "Perhaps scientists must ultimately let go of the ideal of explaining phenomena from first principles and simply accept that complex systems are not always amenable to the classical, reductionist approach" (Heng, 2023).

A primary value of SES modeling for decision-making remains that computers can do what human brains cannot. Even a simple systems model can reveal social-ecological relationships that are not obvious nor intuitive. Yet, the reviews cited here demonstrate that learning, in any capacity, is not a primary focus for most SES models (Groeneveld et al., 2017; Schulze et al., 2017; Drechsler, 2020; Steger et al., 2021). This, perhaps, offers the best site for re-thinking SES modeling work. One promising approach to encourage learning within an SES management context is to integrate computer modeling with 'serious gaming' to allow people to explore options and receive feedback on their choices (see Van der Wal et al. 2016; Xu et al. 2020). Projects like these align well with suggestions that integrated systems models may be most beneficial as boundary objects to help reveal differences in perspectives, to segregate facts about a physical system from beliefs or values about that system, and to resist disciplinary silos (Forrester, 1993; Lorie and Cardwell, 2006; Schlüter et al., 2019; Lindkvist et al., 2020; Steger et al., 2020). As Solomon et al. (2020) note, "models that do the most to advance research and management focus on elucidating concepts and key mechanisms rather than explicitly predicting or explaining observations." Indeed, other recent work on modeling wicked problems, including SES, recognizes the problems with prediction and recommends that modelers be cautious (Polhill et al., 2021; Edmonds, 2023). In short, as Erica Thompson, author of Escape from Model Land, has noted, "models are primarily useful as metaphors and aids to thinking, rather than prediction engines" (qtd in Herndon, 2023). Because they function well as boundary objects, models can help with disciplinary boundary crossing (Mollinga, 2010) to allow broader and deeper attention to the social of social-ecological systems.

All of the reviews cited in this paper suggest a need to expand the social aspects of SES modeling to include theories and/or data from psychology, sociology, cultural anthropology and other social science or humanities fields. While they remain the exception rather than the rule, there are examples of models that integrate social and ecological data beyond simplistic demographics or economic variables. For example, Castilla-Rho and colleagues (2017) combined World Values Survey data with grid-group cultural theory and a groundwater flow submodel into an agent-based model to assess how social norms influence water conservation behavior and the subsequent impacts on groundwater resources. While efforts like this are to be lauded, more sophisticated approaches do create a conundrum because integrating more kinds of data across more disciplines will highlight the complexity of the system(s) being modeled, but at the cost of increasing how complicated the model is. A more complicated model reduces the ability for non-experts (and, frankly, many experts) to understand how it is designed and potentially reduces their ability to engage with the model. This increases the 'black box' nature of models thereby raising concerns for many people about employing that model in any decision context. Advances in artificial intelligence may exacerbate this concern.

This conundrum raises the value of thinking about different levels of SES modeling for different purposes (Cockerill et al., 2007, 2009; Allison et al., 2018; Elsawah et al., 2020). For example, to better understand how any SES functions, it may be most productive to have experts from across diverse disciplines create complicated models that widely and deeply try to capture both social and ecological system complexity (with concomitant uncertainty) as an endeavor in basic science. Although unlikely, information gleaned from such models could be used to support decision-making, if it were translated in an appropriate, receptive context. The greater value in pursuing complicated, basic science type models, however, is to generate better input to populate less complicated models to be used as boundary objects in decision-making scenarios. To meet expectations for transparency these simpler models should be created collaboratively with decision-makers and/or the general public. While less complicated models necessarily sacrifice how system complexity is represented, they can help engage people in exploring system relationships, in generating better questions about the issue at hand, and consequently learning about system complexity and the potential tradeoffs in various decision paths (Voinov et al., 2014; Sun et al., 2016; Allison et al., 2018; Steger et al., 2021). In my experience, the ability for people to learn by creating 'what if' scenarios with SES models was most valuable. Of course, a layered modeling approach still depends on including more robust social data that is actually integrated with physical system data.

To help fill other gaps noted in this reflection, modelers need to heed the suggestions provided in the literature for expanding the social aspects of SES models. At the same time, journal editors and manuscript reviewers need to revisit what is deemed a negative compared to a successful result. Contrary to what some peer reviewers concluded, I feel that all of the modeling projects I worked on succeeded in prompting more complex thought and new ideas for SES management. Frankly, the debates that colleagues and I engaged in were sometimes more informative than the eventual models developed, but this is not well captured in publications about those models. Of course, reviewers, editors, and journals do need to maintain standards of rigor in what they publish, but finding ways to reduce the existing types of bias would enable greater gains toward improving model development and implementation than the current incomplete portrayal of modeling efforts.

To be clear, nothing proposed here is a panacea. There is no 'silver bullet' for designing a modeling process and no model will provide 'solutions' to any wicked problem (Cockerill et al., 2017). Completely capturing social or ecological systems in a modeling context will remain impossible because models are always simplifications of reality. Additionally, there will always be people who insist that there is a singular solution and people who will not accept what even the best models reveal. While SES modeling can be a powerful tool, it cannot reduce the complexity inherent in what is being modeled and it cannot change fundamental aspects of human cognition and decision-making. At best it can help increase what is known about various systems and help make obvious some non-linear, non-intuitive relationships that characterize SES. Hence, modelers need support to pursue deep, complicated models without having to promise predictive capability and without having to shoehorn the process into a participatory effort. Researchers, decision-makers and the public need the freedom to try, and sometimes fail, in developing less complicated SES models as boundary objects. In any model development setting, all participants need to recognize and then set aside any remnants of a mechanistic, linear perspective in developing or implementing an SES model. This may, over time, allow the models created to contribute to more complex decision-making that does not ignore the wicked reality of social-ecological systems.

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