Increasing the uptake of ecological model results in policy decisions to improve biodiversity outcomes

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Abstract

Models help decision-makers anticipate the consequences of policies for ecosystems and people; for instance, improving our ability to represent interactions between human activities and ecological systems is essential to identify pathways to meet the 2030 Sustainable Development Goals. However, use of modeling outputs in decision-making remains uncommon. We share insights from a multidisciplinary National Socio-Environmental Synthesis Center working group on technical, communication, and process-related factors that facilitate or hamper uptake of model results. We emphasize that it is not simply technical model improvements, but active and iterative stakeholder involvement that can lead to more impactful outcomes. In particular, trust- and relationship-building with decision-makers are key for knowledge-based decision making. In this respect, nurturing knowledge exchange on the interpersonal (e.g., through participatory processes), and institutional level (e.g., through science-policy interfaces across scales), represent promising approaches. To this end, we offer a generalized approach for linking modeling and decision-making.

Key Words: biodiversity-ecosystem function relationships; co-production; ecological modeling; policy relevance; stakeholder engagement

Introduction

Ecosystems depend on diverse biological attributes to ensure ecological functions and processes that are fundamental to life on Earth. Improving our ability to represent interactions between human activities and ecological systems is essential to identify pathways to meet the 2030 Sustainable Development Goals (Kim et al., 2018). Therefore, decision-makers often want to anticipate the consequences of policies for ecosystems and human well-being (Isbell et al., 2017). Models are important tools to support such endeavors and can provide a useful way to examine possible outcomes (IPBES et al., 2016). However, examples of modeling outputs that have directly influenced conservation practice and decision-making are rare (Rapacciuolo, 2019). While models are often created with the intention of informing decision-makers, there are a number of factors that may hamper or facilitate the use of the models, and research more broadly, in decision-making processes (Dilling and Lemos, 2011; IPBES et al., 2016; Wall et al., 2017).

Here, we focus on the uptake of biodiversity, ecosystem function, and ecosystem services models. Integrating biodiversity and ecosystem function (BEF) models to improve projections of ecosystem services was one of the main challenges identified in the collective modeling effort that contributed to the IPBES Global Assessment (Rosa et al., 2020), and the insights we share in this paper are drawn from an interdisciplinary SESYNC (The National Socio-Environmental Synthesis Center) working group focused on this challenge. To draw on our collective experience, we informally interviewed working group members that have developed or work extensively with different ecological models about their model use experience.

Working group members have experience with a variety of ecological models with varying levels of uptake in policy processes at different scales, which provided a unique opportunity to compare factors hampering and facilitating model uptake. Models ranged from national fisheries management (e.g., Atlantis in Australia; (Elizabeth A. Fulton et al., 2014)) to regional water management and land use planning (e.g., INVEST; (Daily et al., 2009; Kareiva et al., 2011; Nelson et al., 2009) (See list of models in appendix 1). Nearly half of the models discussed had not yet been used in a specific decision-making process.

Drawing on this expert opinion and reflection, we present lessons learned for how to improve ecological model uptake for decision-makers, and go further to emphasize that it is not simply uptake, but active and iterative involvement by stakeholders that can lead to more impactful outcomes. This is especially important as we move into the negotiation of the post-2020 Global Biodiversity Framework for the Convention on Biological Diversity (CBD), where there is a huge reliance being placed on the ability of models to identify challenges and to answer key questions, especially in monitoring progress towards specific targets. For example, models are being used to explore possible pathways to reversing biodiversity loss by 2050 (Leclère et al., 2020). Here, we present key considerations to ensure that models are better able to meet policy needs. Although many of the concepts we present are not new (e.g., (Rose et al., 2020), there is a persistent need to raise awareness of these issues and potential solutions among the modeling community (Addison et al., 2013; Rapacciuolo, 2019; Saltelli et al., 2020). Enhanced consideration of these issues by ecological modelers may improve the usefulness of modeling results in decision-making - allowing models to reach their full potential by providing decision-makers with a stronger evidence basis for making decisions in often highly uncertain contexts.

Facilitating and Hampering Factors

We categorized the factors facilitating and hampering the use of models into three main categories: technical, communication, and process-based (i.e. related to the social context of decision-making) factors. These mirror the characteristics of actionable information identified by Cash et al. (Cash et al., 2003) -- credible, salient, and legitimate -- but are distinct in that they are specific factors related to modeling, which may or may not lead to information uptake.

Technical factors are often the focus of modeling work (e.g., improving model accuracy, precision, and data processing techniques, addressing data gaps). From the technical perspective, issues which can either facilitate or hamper model uptake span the entire modeling process, including the thematic focus or scope of a model, as well as model assumptions, resolution, and scale (spatial and temporal). Model relevance is often more context dependent than discussed, so it is important to assess whether the model is fit for purpose in each context where it is being used (Parker, 2020). Most models that had been used in a policy context had underlying data and/or model results that matched the scale of the decision. Crucially, the general model framing - in terms of implicit or explicit value judgements by the modelers and model designers - may underpin the additional technical barriers outlined below.

While most models did not incorporate BEF relationships, modelers deemed them to be important to include depending on the decision. Better incorporation of these relationships could improve model accuracy, especially over longer time frames where it is important to capture all relevant processes in the model. For example, an Australian ecosystem modeling exercise that ran more traditionally structured marine ecosystem models alongside models including species turnover found very different results under various potential levels of climate change (Fulton and Gorton, 2014). Biodiversity-productivity relationships have also been found to be important for both biodiversity conservation and climate mitigation (Mori et al., 2021). In other cases, the potential imbalance between model complexity and the perceived usefulness of output could act as a hampering technical barrier; for instance, incorporating BEF relationships into INVEST models used for mapping water supply may not be useful, because the policy-driven question may not be directly impacted by this relationship, and including it may make the model unnecessarily complicated. There is a long history of work in fisheries showing that the complexity of models used in decision making must be compatible with the level of available information, with more constrained models containing key relationships leading to more effective management decisions than more complicated models based on sparse information (Ludwig and Walters, 1985). However, it is important to update models as new data and understanding of underlying relationships become available (Myers et al., 2021). Ultimately, our interviews highlighted that the BEF link is currently lacking in most models but would be especially important to better understand the consequences of climate change and other global changes for ecosystem services. A key reason for this is because it is the change in biodiversity over time, within a place, that is expected to impact ecosystem services. BEF experiments assess this relationship, which could otherwise be masked by only comparing ecosystem services between sites (Loreau, 1998; Tilman et al., 2014).

Communication and accessibility-related factors facilitating or hampering the uptake of models and their outputs included the accessibility of the model design (e.g., how the model design and assumptions are communicated), the accessibility of the modeling interface (e.g., the steepness of the model interface learning curve), as well as the accessibility of the modeling output (e.g., how difficult the modeling products are to understand, to be updated and to maintain accessibility in time). Models that lack flexibility or are difficult to use can discourage decision-makers (Robinson and Freebairn, 2000). Another key factor is transparency or clarity in addressing the uncertainties related to a model -- scientific uncertainty does not necessarily decrease trust (van der Bles et al., 2020), but the way in which it is communicated is influential (Howe et al., 2019). Adding precise numbers to uncertain predictions can lead to a false sense of accuracy in the results (Saltelli et al., 2020). On the decision-maker side, there is also a tendency to confuse uncertainty, where the probability of a situation is unknown, with risk, where the confidence in probabilities is known. This can lead to overconfidence in policy options and business as usual practices (Stirling, 2019). All of these points make communication fraught and the situation is only exacerbated by the incompatibilities in the cultural and communication styles of scientists and decision-makers (Cairney, 2016); this is why knowledge brokers, who can successfully interpret between the two groups, are such a critical part of modern modeling teams (Cvitanovic et al., 2015).

While the majority of available studies on factors facilitating and hampering model uptake in decision making focus primarily on technical and communication factors, this perspective illustrates the key role of **process-based** factors. These factors have been frequently underestimated or overlooked in different modeling communities. However, their importance has been increasingly recognized (e.g., (Clark et al., 2016)) and warrants deeper consideration, as they represent some of the key barriers to a larger-scale model uptake in decision making.

The issues related to the social context of model uptake cover a broad range of process-related aspects. On the institutional level, model uptake is determined by how decision-making processes are embedded in institutional structures, as well as by institutional arrangements, bureaucracy and power distribution. Understanding how decisions are made and who is affected by decisions (i.e., identifying stakeholders) is a key part of problem framing in the decision making process, and is important for modelers to understand as they define the modeling problem (Figure 1; (Runge, 2020). On the level of individuals, interpersonal relationships have proved influential in the process of knowledge transfer. Another role of the social setting lies in which and whose objectives define the modeling process, and which and whose values and priorities tend to be incorporated (both on the level of individuals and social groups). For example, a multi-species size spectrum model implemented in MIZER was designed by a team that included scientists working in government agencies to address policy-driven questions, which facilitated its use in identifying large fish indicators for use in the North Sea (Blanchard et al., 2014; Scott et al., 2014). Finally, the skills and capacities of decision-makers to use a particular model and its interface may present additional barriers. Both institutional- and individual-level factors can be exacerbated by the tendency to follow path dependencies and the lack of ability or willingness to change practices (e.g., reliance on models already in use) (Fulton, 2021).

Process-based factors can facilitate model uptake by building a sufficient level of understanding of a model and/or its underlying concepts and mitigating the fear of excessive sophistication and complexity, and thus nurturing trust in models and modeling. However, social context and process-based factors can also underlie decision-makers' hesitation of modeling results (e.g., fear of getting less funding in the light of modeling results or making potential management failures more apparent, and mistrust of results that do not align with previously held beliefs; (Pahl-Wostl, 2009)). Conversely, modelers highlighted that a robust participatory process with stakeholders, identifying policy-driven questions that underpinned model development and output, and sufficient capacity to increase model usefulness facilitated model uptake. Identifying shared goals and designing a collaboration process up front can help address these issues (Hallett et al., 2017; Lawson et al., 2017). While there are many benefits to participatory approaches, modelers should also be aware that including decision-makers in the process could lead to a perception of less objective science, especially if only a small group of stakeholders are involved (Enquist et al., 2017)).

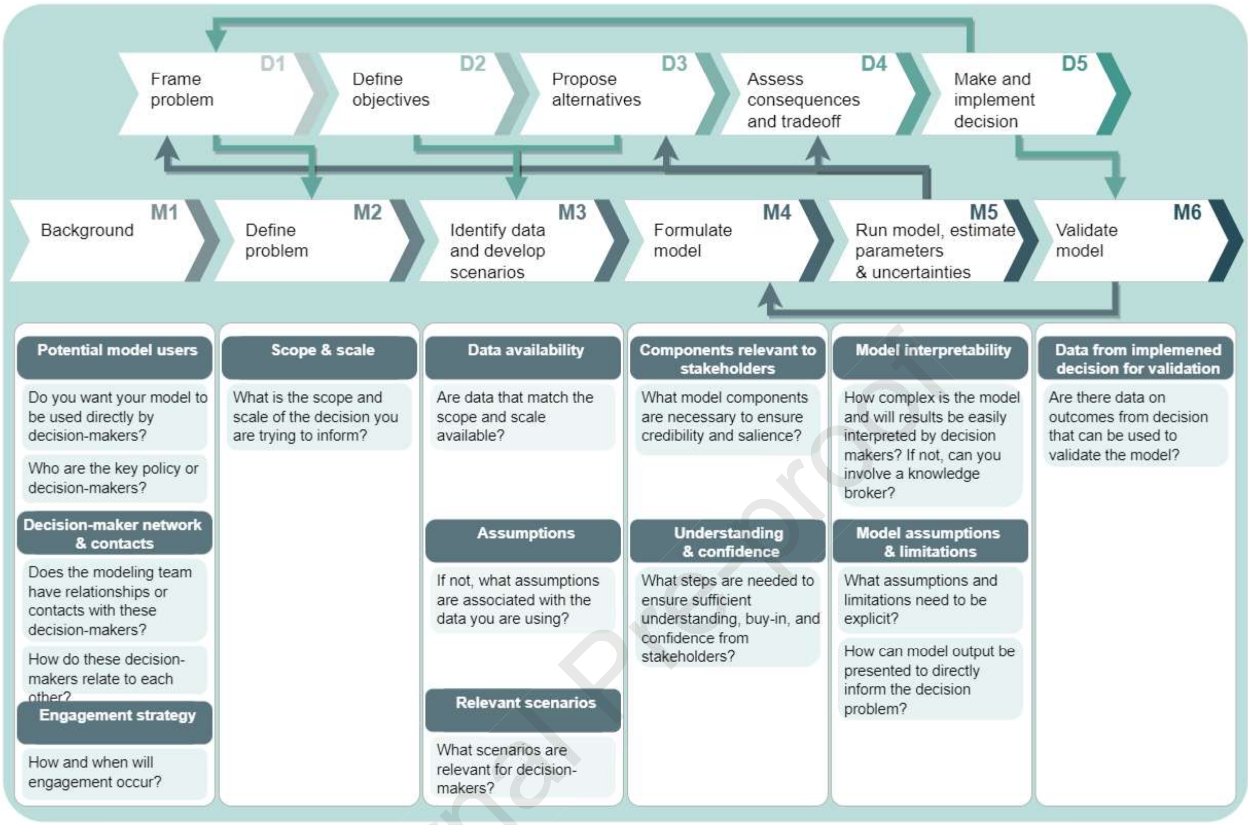

Figure 1: Stronger linkages between modeling and decision-making processes can lead to more effective decisions. The upper row represents steps in the decision-making process (D#), and the bottom row shows the modeling process steps (M#). Arrows show connections from the decision-making process (D) to the modeling process steps (M) and vice versa. In a structured decision making process (Runge, 2020), decision-makers can inform the modeling process by defining the problem and objectives, proposing feasible alternative actions, and by providing data to validate models after decisions have been implemented. In turn, model outputs can be used to assess consequences and tradeoffs of proposed actions, identify possible alternative actions that might achieve objectives, and even lead to re-framing or identifying new decision problems. Although presented linearly, the steps in the modeling and decision-making cycle are not necessarily linear. Questions to help guide model development are provided below each step. *Although the questions are organized according to the steps in the modeling process, they should be considered at the outset of the modeling work.*

Lessons learnt for improving the process of model design and use

Based on our collective experience, we reflected on what could have been done differently to improve uptake and identified three areas for consideration. We discuss these lessons in light of literature that provides more detailed suggestions of ways to facilitate model uptake.

1. *Identify and include decision-makers from the beginning and during the entire process*

Including policy and other decision-makers throughout the research process (i.e., the co-production of knowledge) enhances its legitimacy and relevance to decision-making purposes (Meadow et al., 2015), thus helping to reduce the impact of hampering process-based factors. Descriptions of and considerations for applying translational ecology approaches that include relevant decision-makers and interdisciplinary perspectives have been described elsewhere (e.g. (Enquist et al., 2017; Rose et al., 2020; Wall et al., 2017)), but applications in the modeling context remain uncommon ((Rapacciuolo, 2019); but see (Beier et al., 2017) and (Miller et al., 2017) for recommended practices for co-producing science in general and models in particular, respectively.

Including users who understand the policy environment in the model design *ab initio* means that the model inputs do not have to be retrofitted for a specific outcome later, thereby saving time and effort. For example, setting up a participatory process with all interested parties from the beginning to get consensus on the technical aspects of the work (data, targets, decision support systems) helped facilitate the successful use of species distribution modeling for forest planning in New South Wales, Australia (Ferrier et al., 2002a, 2002b; Finkel, 1998). In instances where directly involving stakeholders in the design is not feasible (e.g., when the model is too complicated), another mechanism to bridge the model-decision divide is through the use of a knowledge broker (Chapman et al., 2017; Safford et al., 2017). As a go-between, a knowledge broker will have sufficient knowledge of the model dynamics to be able to feed information and needs to/from stakeholders. Indeed, active participation from stakeholders throughout the modeling process may not always be necessary; there is a spectrum of stakeholder engagement approaches, all of which can lead to actionable science (Bamzai-Dodson et al., 2021).

Figure 1 presents an example of how modeling and decision-making processes can be linked. Although presented as a linear process, engagement with stakeholders can be initiated at various parts of the modeling cycle depending on the decision-making scale, goals of the modeling exercise, and overall understanding of the modeled processes. For example, when general understanding of our ability to model particular relationships (e.g., BEF relationships) is low, it may be appropriate to engage stakeholders after initial model development has been completed, when preliminary outputs can be used to raise awareness of new or improved information and thus help reframe the decision-making problem. Moreover, decision-making processes and relevant model outputs are different at the global scale, which often focus on the evidence base for setting global targets, versus regional and local scale, where on-the-ground management decisions are made; thus, models or outputs that have been developed for one scale of decision-making may need to be retrofitted for applications at other scales. Stakeholder mapping can be used to determine which decision-making scale and stakeholder groups may be most interested in the model results.

2. *Communication with decision-makers*

Communication with key decision-makers, whether they are local managers or government ministers, is vital to any model uptake strategy. First, it is important to create a common understanding of language and culture between modelers and decision-makers (Jackson et al., 2017); techniques like the persona method are useful to characterize user needs and design solutions (Cooper, 1999). For models that are relatively easy to use, seeking opportunities to introduce the model to decision-makers, investing in capacity building, and letting them explore it for themselves is a good way to get a richer understanding of what the model can and can't do and what it's best used for. For more complex models, it may be necessary to communicate higher-level model structure; in particular, modular designs can facilitate model communication and customization. Regardless of model complexity, communication should involve transparent descriptions of model limitations and uncertainty without belaboring the technical details. It is important to be transparent about the assumptions and value judgements made by the modelers in model framing and highlighting how those decisions affect model output (Saltelli et al., 2020). Uncertainty can be communicated verbally rather than numerically; scales such as the Intergovernmental Panel on Climate Change's seven-point likelihood scale may be preferable for stakeholders (Rapacciuolo, 2019). These facilitating factors are supported by ensuring that models, or at least model outputs, are open access.

3. *Iterative learning and model evaluation*

Continuously improving models as new data becomes available can lead to better decision outcomes (Myers et al., 2021). In retrospect, it is easy to see where research gaps could have been covered by the model if certain aspects had been included, for example analyzing biodiversity impacts outside of protected areas to be able to appreciate the net-outcome for biodiversity of interventions in the New South Wales case (Ferrier et al., 2002a, 2002b; Finkel, 1998). Sometimes including different scenarios at an earlier stage in the model can be helpful for exploring a wider set of futures, and extending the models to include multiple drivers of change can also be more relevant for decision-makers. Incorporating diverse user values and objectives into modeled scenarios (e.g., Nature Futures Framework; (Kim et al., 2021; Pereira et al., 2020) and getting feedback on plausible alternative actions can make model outputs more relevant for users. A critical aspect of the modeling process itself is also to evaluate the model. The extra effort of evaluation is rewarded by increased transparency and credibility of the overall approach and sets up a learning process for later improvements (Dietze et al., 2018). If decision-makers use model output to select and implement a decision, monitoring decision outcomes can provide useful data for model validation (Figure 1).

Box 1. Atlantis-SE: An Example of Successful Model Development and Use

Overview

The Atlantis modeling framework is a marine ecosystem model that has been used to evaluate management strategies and to inform marine ecosystem-based management decisions. The model includes two-way coupling of all components of the adaptive management cycle, ranging from socioeconomic drivers (market, gear choice) to the biophysical system (climate, mortality) and is intended to be used alongside others to assess system uncertainty. Atlantis has been applied to many management decisions in Australia and the United States. For example, a national-scale project in 2007 aided in the restructuring of south-east Australian federal fisheries. The decision process assessed actions and their consequences, trade-offs between costs and benefits, uncertainty, and the type of monitoring needed.

Model Decision and Context

In 2004, it was becoming clear that management measures in place were insufficient to address the poor economic performance and decreased ecological health of Australia's Southern and Eastern Scalefish and Shark Fishery (SESSF). Stakeholders of all backgrounds acknowledged the need to re-evaluate management options. A stakeholder-scientist collaboration stepped through a qualitative foresighting scenario exercise, exploring alternative "whole-of-system" management strategies, and in parallel oversaw a quantitative evaluation of the key management strategies using Atlantis Southeast Australia (Atlantis-SE). The strategies tested ranged from status quo to conservation-dominated management. After considering trade-offs between priorities, no single management solution proved beneficial, though a strategy that used a balanced set of actions performed well all around and ultimately inspired the aforementioned restructuring of SESSF and the form of management now in place in the fishery (Elizabeth Ann Fulton et al., 2014)). The approach worked so well that various versions of this Atlantis model have been used over the past decade to explore other issues and options for the fishery (e.g., (Fulton et al., 2016; Pethybridge et al., 2020).

Things That Worked Well

The modeling process of Atlantis successfully allowed for analysis of multiple scenarios and drivers of change. The modular nature of Atlantis gave the users choice of model formulation, so they were able to set complexity at their desired level. Despite the large number of possible management options that could be tested, stakeholders established project goals early on; this produced a few feasible strategies rather than overwhelming decision-makers. Model uncertainty was communicated effectively with stakeholders by making the results of model runs readily accessible. The success of Atlantis was also attributable to consulting often with a broad range of stakeholders from start to finish. The model was calibrated and validated against available datasets for the region (using training and test set approaches), largely catch and effort data sets from the fishery, but also available diet and habitat data and observations of charismatic megafauna (seabirds and marine mammals; (Fulton et al., 2007)). Overall, the Atlantis-SE project successfully aided in the restructuring of Australian fisheries, due to precise model parameters and goals, engagement of stakeholders throughout the project, and communication of findings and uncertainty with decision-makers. The long ongoing collaborative relationship between fisher representatives, managers, NGOs, and scientists in the region, due to the participatory management system used in the fishery, was likely the strongest reason for the success of the work overall.

Conclusion

Models provide a useful way to assess how policy decisions may impact biodiversity and ecosystem services. However, no model can capture all aspects of a system. As noted by George P. Box, ‘All models are wrong but some are useful’. The ‘wrongness’ of models pose a big challenge to decision-makers, whose choices affect people's lives and environments. Acknowledging implications of the model being wrong is important; can a robust finding be made even if the model is imperfect, or could there be serious consequences of an incorrect prediction? It is therefore important not just to communicate model uncertainties, but to work actively with the intended users of the model outputs in unpacking assumptions and be open to reconfiguration so as to make sure that the models ‘wrongness’ does not stop it from being useful.

The recent IPBES global assessment highlighted that transformative changes are needed to halt biodiversity loss and sustain nature’s contributions to people (Díaz et al., 2019)). As part of the transformative change, it is important to move towards transdisciplinary work with the active participation of the different stakeholders (Clark et al., 2016; Grumbine and Xu, 2021). While our understanding of how biodiversity contributes to human well-being has grown, many models do not yet fully incorporate this relationship. Nevertheless, focusing only on technical model improvements will not be enough to bring about transformative change for biodiversity. While there is still an important role for traditional modeling approaches (e.g., for improving scientific understanding), investing in the process surrounding a modeling exercise and promoting two-way interactions between modelers and stakeholders is vital for successfully contributing to decision-making processes. In particular, trust-building and establishing relationships with decision-makers have proved key to increase buy-in to modeling as a key element for knowledge-based decision making. In practice, this means working closely with those involved in decision-making on the ground and at community levels, as well as at higher policy-making levels. In this respect, nurturing knowledge exchange on the interpersonal level (e.g., through participatory processes), and on the institutional level (e.g., through promoting science-policy interfaces across scales), represent promising approaches.

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Declaration of interests

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