Ecosystem Services xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Ecosystem Services

journal homepage: www.elsevier.com/locate/ecoser

Transparent and feasible uncertainty assessment adds value to applied ecosystem services modeling

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ARTICLE INFO

Keywords:
Best practice
Ecosystem service
Fit-for-purpose
Impact assessment
Uncertainty
Validation

ABSTRACT

We introduce a special issue that aims to simultaneously motivate interest in uncertainty assessment (UA) and reduce the barriers practitioners face in conducting it. The issue, "Demonstrating transparent, feasible, and useful uncertainty assessment in ecosystem services modeling," responds to findings from a 2016 workshop of academics and practitioners that identified challenges and potential solutions to enhance the practice of uncertainty assessment in the ES community. Participants identified that one important gap was the lack of a compelling set of cases showing that UA can be feasibly conducted at varying levels of sophistication, and that such assessment can usefully inform decision-relevant modeling conclusions. This article orients the reader to the 11 other articles that comprise the special issue, and which span multiple methods and application domains, all with an explicit consideration of uncertainty. We highlight the value of UA demonstrated in the articles, including changing decisions, facilitating transparency, and clarifying the nature of evidence. We conclude by suggesting ways to promote further adoption of uncertainty analysis in ecosystem service assessments. These include: Easing the analytic workflows involved in UA while guarding against rote analyses, applying multiple models to the same problem, and learning about the conduct *and value* of UA from other disciplines.

1. Introduction: Why promote "transparent, feasible, and useful" uncertainty assessment?

1.1. Background and motivation

Over the last decade, as the ecosystem services (ES) framework has proliferated, multiple researchers have expressed the need for ES analysts to improve consideration of the uncertainties that are embedded in applied modeling efforts (Seppelt et al., 2011; Hou et al., 2013; Hamel and Bryant, 2017). There are signs trends may be moving in the right direction, reflected by recent articles giving significant attention to major uncertainty, sensitivity, and validation issues in the ES realm (e.g. Santos de Lima et al., 2017; Bagstad et al., 2018; Ochoa and Urbina-Cardona, 2017). However, we do not yet have evidence that context-appropriate uncertainty assessment[1] is becoming a routine part of ES modeling practice.

Hamel and Bryant (2017) argue that, while there are a few legitimate challenges specific to conducting uncertainty assessment (UA) in the ES realm,[2] for the most part relevant methods exist and are more commonly applied within other disciplines (e.g., hydrology and policy analysis, and the broader realm of integrated environmental modeling, cf Refsgaard et al., 2007; Bennett et al., 2013; Uusitalo et al., 2015). Though the use of comprehensive and consciously-framed UA may not be routine in these other disciplines (see, e.g., Guillaume et al., 2017 in the water resources realm), it does feature more prominently, and modelers are able to draw on at least some default UA techniques within their respective discipline. This raises two questions: Why are these methods not more widely adopted within the ES realm, and what

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[1] As in Hamel and Bryant (2017, p. 2) we "use 'uncertainty assessment' as an umbrella term including problem scoping, qualitative treatments of uncertainty, and formal quantitative analysis techniques" – including sensitivity analysis, and also verification and validation efforts.

[2] Namely, that typical ecosystem services assessments are fundamentally spatial, biophysical and social all at the same time.

https://doi.org/10.1016/j.ecoser.2018.09.001
Received 19 June 2018; Received in revised form 31 August 2018; Accepted 5 September 2018
2212-0416/

can be done to promote adoption of context-appropriate uncertainty assessment?

These questions were explored as part of a three-day workshop held in November 2016 at the National Center for Socio-Environmental Synthesis (SESYNC), in the United States. Bringing together 18 academics and practitioners (including most authors of this article), this three-day workshop systematically identified many challenges limiting widespread adoption of UA by ES practitioners, as well as ways in which those challenges could be addressed (Bryant and Hamel, 2017). While the group determined a host of interacting causes and potential solutions, most causes could be categorized under two broad justifications: that UA was perceived as "too hard" to conduct (i.e., too time consuming relative to available resources, or requiring sophisticated methodological skills), or relatedly, not worth doing (i.e., even when done, UA is not likely to change conclusions or affect decisions). Among other recommended solutions, participants determined that a set of clear and compelling case studies showing the feasibility and value of UA could help address this problem. To do so, such a set would include cases demonstrating that UA can be feasibly conducted at varying levels of sophistication, and that such assessment can usefully inform decisions or research conclusions, rather than just put ranges on the predicted outcomes or valuations – in other words, that UA can provide useful information and build confidence, rather than just complicate or obfuscate. As indicated by its straightforward name "*Demonstrating transparent, feasible, and useful uncertainty assessment in ecosystem services modeling,*" this special issue aims to serve as such a collection.

We recognize that the issue of promoting uncertainty assessment is a many-faceted one – in terms of what success looks like, and in the pressures, incentives and constraints facing analysts and the stakeholders with whom they interact and communicate (see Merritt et al., 2017 for a useful collection of examples). Many of these complications are illustrated by articles in this special issue and also detailed in Section 2.5 of the workshop report (Bryant and Hamel, 2017). What is appropriate is also context- and resource dependent, with different techniques and levels of effort appropriate at different times for different decisions. But overall, some assessment of model adequacy for the purposes to which the model may be put is critical – not just for the quality of scientific findings, but also for communication and legitimacy in the eyes of stakeholders (Willcock et al., 2016). Formal or not, sophisticated or not, consideration of uncertainty plays an important role in such assessment.

1.2. Purposes of this article and special issue

Given the above, we created this special issue under an open call, to serve as a resource with two related but distinct purposes:

- Provide exemplar cases of the many ways that uncertainty analysis can be conducted ("transparent and feasible").
- Provide a succinct body of articles that demonstrate why it is useful to conduct uncertainty analysis in the ES realm ("useful").

The contributions of some articles lean more heavily to the first bullet and some more to the second. Different readers will find different value in the assembled articles, depending on their background and the way in which they interact with the modeling process (e.g., as analyst, project manager, scientist, stakeholder, or decision-maker). Some may be exposed to new methods, and some will be inspired to try methods with which they only had loose familiarity, but which they had not considered worth understanding deeply enough to implement. Above all, we hope that many readers will find convincing demonstration of the value that uncertainty assessment can bring to a modeling effort. For those already convinced, we hope they will find helpful material with which to engage others on this topic.

This article itself aims to (1) orient the reader to the content of the special issue while drawing out key messages on the practice and utility of uncertainty assessment, and (2) provide critical reflections in the form of lessons and recommendations on remaining challenges and how to overcome them. These are based on the included articles as well as our own experiences as applied ES modelers and participants in the SESYNC workshop noted above.

2. Overview: Diverse applications, modeling methods, and approaches to uncertainty assessment

2.1. Orientation to articles

This special issue presents papers spanning a broad array of methods and application areas, with domains including forests, fisheries, cultural landscapes, urban green infrastructure, and others. On the methods front, it includes examples ranging from simple variation of input data, to Monte Carlo methods combined with stochastic dominance tests, to scenario considerations treated probabilistically, to those treated with participatory assessment. The work described includes ES modeling approaches that encompass process-based, proxy-based,[3] and qualitative considerations, and covers applications on four continents. Table 1 provides an overview of the key dimensions of each article, and in the text below we draw out key lessons for the ES community, focusing in particular on the "useful" aspect of the uncertainty analysis.

The issue begins with a review article (Baustert et al., 2018, this issue) that many readers unfamiliar with formal conceptions of uncertainty may find useful for assessing the special issue papers and considering uncertainty in their own work. Baustert et al. describe and cross-walk the steps, frameworks and elements of uncertainty assessment that have already been brought forth in the literature, orienting the reader to common concepts and terminology and where they differ (e.g., those of Walker et al., 2003; Refsgaard et al., 2007; Warmink et al., 2010). They review sources of uncertainty, help interpret the underlying frameworks, and their overview can assist an analyst in judging whether the nuances of the different frameworks are important for their work. Their paper will also help readers of other articles in this special issue consider uncertainty more systematically.

The remainder of the papers all demonstrate a complete or partial ecosystem services assessment that includes an examination of one or more key uncertainties, and how those uncertainties can be treated using available methods. As Table 1 provides a concise overview of topics and methods, we do not explicate these further, but instead use the rest of this section to highlight how the articles demonstrate the value of uncertainty assessment.

2.2. Demonstrating how uncertainty assessment can matter

To realize the goals of the special issue, this section highlights the ways in which the uncertainty-oriented analysis in the papers provides benefits to modelers and potential stakeholders. Note that these are not necessarily the primary contributions of the papers mentioned, but rather, our view of key points related to UA. We of course encourage readers to review Table 1 and examine abstracts of the relevant papers to read them for their own substantive contributions as well.

2.2.1. More complete uncertainty assessment can change the recommended course of action

Changing the recommended decision is perhaps the most obvious and compelling way that UA could make a difference in a modeling

[3] Adopting the language of Lavorel et al. (2017, p. 243) we "define proxy models as models that relate ES indicators to land or marine cover, abiotic and possibly biotic variables by way of calibrated empirical relationships or expert knowledge." A classic example would be assuming particular levels of provisioning or carbon sequestration are associated with each category in a land-use/land-cover map.

Table 1
Overview of included articles, by author, title, application, and key methods used.

First author	Title	Application area	Geography	Methods illustrated
Baustert	Uncertainty analysis in integrated environmental models for ecosystem service assessments: Frameworks, challenges and gaps	Review	NA	Uncertainty frameworks
Martin	Non-monetary valuation using Multi-Criteria Decision Analysis: Using a strength-of-evidence approach to inform choices among alternatives	Wetland siting	New England, USA	Outranking methods for multi-criteria decision making
Harmáčková	Future uncertainty in scenarios of ecosystem services provision: Linking differences among narratives and outcomes	Long-range landscape planning	Czech Republic	Participatory qualitative to quantitative scenario translation; land use change modeling; ES bundle analysis
Maldonado	Probabilistic modeling of the relationship between socioeconomy and ecosystem services in cultural landscapes	Service provision in cultural landscapes	Andalusia, Spain	Object-Oriented Bayes Networks; Scenario framing with Bayesian approaches
Willcock	Machine learning for ecosystem services	Firewood/provisioning, biodiversity	South Africa, Sicily	ARIES/BayesNets
van Soesbergen	Uncertainty in data for hydrological ecosystem services modelling: Potential implications for estimating services and beneficiaries for the CAZ Madagascar	Hydrologic ecosystem services	Eastern Madascar	Hydrologic modeling; LULC scenario analysis;
Morzaria-Luna	Diet composition uncertainty determines impacts on fisheries following an oil spill	Fisheries	Gulf of Mexico	Dynamic ecosystem modeling, emulator, stochastic analysis
Monge	Implications of future climatic uncertainty on payments for forest ecosystem services: The case of the East Coast of New Zealand	Forestry, soil & carbon regulation	New Zealand	Economic optimization, Monte Carlo, stochastic dominance, net present value CDFs
Vauhkonen	Uncertainties related to climate change and forest management with implications on climate regulation in Finland	Forestry – carbon offsets	Finland	Climate uncertainty, Markov chains
Huber	Improving confidence by embracing uncertainty: A meta-analysis of U.S. hunting values for benefit transfer	Recreation (hunting valuation)	Continental United States	Benefits transfer, meta-regression
Ashley	Including uncertainty in valuing blue and green infrastructure for stormwater management	Urban – Blue and Green Stormwater Infrastructure	United Kingdom	Sensitivity analysis, Robustness assessment

effort – and while it does not always happen, there are cases where combinations of better data and assessment processes led to alternate recommendations. Using European Union climate policy around forest carbon sequestration as a case study, Vauhkonen and Packalen (2018, this issue) demonstrate how common default assumptions regarding forest management can lead to inefficient outcomes compared to approaches that consider the ways in which future trends on climate interact with forest management. By highlighting the dependence on management with a dynamic model, they show how better consideration of interacting management actions and external forcings can have significant benefits for policy implementation (sequestering up to one third more carbon), and thereby contribute to more effective climate mitigation efforts.

Morzaria-Luna et al. (2018, this issue) use Monte Carlo simulations and a statistically-derived emulator to better consider uncertainties in a large dynamic aquatic ecosystem model (Atlantis), with a focus on the response to an oil spill. The analyzed model is used, among other purposes, to make damage assessments in lawsuits, so the outputs can have considerable policy impact. Their thorough analysis of the impact of uncertainties reveals plausible conditions under which the impact following an oil spill could actually be positive for some fisheries, contrary to intuition. In this case, their final analysis did not “flip the sign” of the *expected* impact from net damages to net benefits, although UA may do so under other conditions. It also revealed complex dynamics and high sensitivities to uncertain input data that can guide future efforts to estimate key policy-relevant outcomes, such as damage assessments.

Monge et al. (2018, this issue) provide an example that illustrates the role of probabilistic risk characterization in determining the appropriate course of action. They combine deterministic exploration of discount rates with probabilistic (Monte Carlo) modeling to map out how stakeholders with given discounting and risk aversion profiles should prefer each of three erosion and carbon-oriented reforestation strategies in coastal New Zealand. Using a variety of what are called “stochastic dominance tests” (a tool for comparing options under risk), they map these profiles to public and private entities, and show how their discount rates affect the preferred option. They also show that climatic uncertainty changes the level of return required for programs to be cost-effective. These results provide a compelling case of how complex numerical modeling can still be distilled to simple decision-relevant lessons.

2.2.2. *Promoting transparency via uncertainty assessment allows decision-maker assessment of appropriate confidence levels*

A slightly more subtle – but still highly valuable – benefit of uncertainty assessment is that it can make it easier for stakeholders to comprehend the implication of model results within the broader context that they are navigating. That is, by more diligently exposing and exploring a model, as is required for uncertainty assessment, modelers can improve transparency of the model and also illuminate how specific conclusions are dependent on assumptions of varying credibility. Even when these implications may not be “formally” assessed, they can still have value to stakeholders – and to modelers, who may improve models or collect additional data as a result.

In this vein, Harmáčková and Vačkář (2018, this issue) show that diversity in narrative scenarios does not necessarily translate into diversity in quantified scenarios. Using the example of a UNESCO biosphere reserve located in the Czech Republic, they show how, during the process of capturing and then quantifying participatory scenarios of landscape futures, the diversity of outcomes is narrowed. The implication here is that analysts and decision-makers need to carefully consider the issue of “false robustness” – i.e., they may think that certain policies work well in a variety of plausible futures (as captured by narrative scenarios), when in fact the futures they have explored do not vary as significantly when actually considering the numbers. In their case, the convergence occurs due to a combination of assumptions in how qualitative scenarios of future development paths are translated into land use scenarios, and in the mechanics of how land use scenarios propagate through ecosystem service models.

Somewhat conversely, Huber et al. (2018, this issue) show how seemingly disparate final metrics of interest may not be significantly different from each other. They conduct a meta-analysis of valuation studies to identify the economic value of hunting opportunities for different animals in different regions of the United States. They apply a meta-regression approach and show that the application of confidence intervals from the meta-regression reveals that in many cases non-trivial differences in valuation estimates are actually contained within wide uncertainty ranges – ranges that would be difficult to identify without the meta-regression framework. Therefore, what may seem like differences that would guide prioritization of one action over another may not be grounds for doing so, meaning that ancillary considerations could justifiably hold more sway over a decision process.

Ashley et al. (2018, this issue) inventory and quantify uncertainties in an ecosystem service valuation tool for blue and green stormwater infrastructure (B£ST[4]), and explore how these uncertainties influence outcomes directly within the tool. The analytic techniques included vary in their level of sophistication, from straightforward sensitivity analysis using default scalars on benefits, to proxy indicators for flexibility of the system, to allowing for stakeholder-based or analyst-based scenario and robustness assessment. By making uncertainty considerations a prominent part of the tool interface, the approach helps the analyst keep uncertainty at the forefront of the process and provides important contextual information for decision-makers. In their case study, applied to a blue and green infrastructure proposal in Leeds in the United Kingdom, they show that accounting for estimates of how transferable database benefit values are to the design context dramatically scaled down the benefit estimates, though the blue and green infrastructure option still outperforms piped drainage systems. They also use an index-based approach to show that adaptability of the green infrastructure design to future conditions ranks more highly than piped drainage, but not drastically so – suggesting that decision-makers will need to be proactive to ensure that performance will be maintained depending on the future that emerges.

In the context of multi-criteria decision support, Martin and Mazzotta (2018b, this issue) show how outranking methods can facilitate more transparent comparison of options under consideration. In their case, they are helping decision-makers prioritize among a small set of wetland restoration projects to undertake, where each site is ranked on 22 benefit indicators in five categories, which are not obviously directly comparable (e.g., flood water regulation and bird watching opportunities). Outranking methods are a class of multi-criteria decision aid that allows for fuzziness and varying strength of evidence in stakeholder preferences themselves. It facilitates greater transparency in part by eliciting values in the process of directly comparing outcomes associated with specific options, rather than assuming pre-existing preference structures can be captured with precision (e.g., economic utility functions, or trade-off weights).

Martin and Mazzotta also clearly identify the ways in which different choices should be contingent on particular preference combinations that were mapped by stakeholders to anticipated funding scenarios. Highlighting such dependencies helps stakeholders better think through their problem. Their related work outside of this special issue (Martin and Mazzotta, 2018a) also touches on the issue of false robustness mentioned earlier: They show that even within a common conceptual framework of scoring and aggregating multiple ES outcomes, plausible and similar-seeming alternatives for aggregation result in the recommendation of different management alternatives – a fact that would not be illuminated without the comparison across aggregation methods, which could be considered a form of sensitivity analysis for a multi-criteria decision aid.

More broadly, by characterizing uncertainty transparently, UA allows decision-makers to set their own thresholds of what level of uncertainty is acceptable for their decision context. They are then able to use their own judgement for potentially contentious decisions, where uncertainty is higher and may involve a mix of uncertain values and outcomes. For example, in the context of prioritizing land for its ability to provision biodiversity and ecosystem services, Willcock et al. (2018, this issue) suggest that while it is relatively obvious that highly certain, high value ES sites should be appropriately managed, it is unclear which sites should be the next highest management priority. They ask whether a medium-ES value site with high certainty or a potentially high-value site with medium or low certainty should be the next priority, which is essentially a question of values and risk tolerance, which cannot be posed in the absence of UA on the ES provisioning levels. Willcock et al. highlight how machine-learning techniques and Bayesian networks can be used to perform UA to distill the choices facing decision-makers.

Other papers demonstrate what may be considered more "classical" uncertainty assessment in the form of exploring whether key input variables to the modeling process can have significant impacts on model results, while showing how sensitivity can be highly dependent on the metric used. Morzaria-Luna et al. (above) provide a complex example, while van Soesbergen and Mulligan (2018, this issue) demonstrate that the uncertainty methods do not need to be complex to be useful. They explore how six different spatial precipitation datasets affect the predicted runoff in a region of Madagascar, under baseline conditions and under a common deforestation scenario (though runoff is not an ecosystem service, it will heavily drive multiple other ecosystem services). In addition, they consider the potential impact that population datasets may have on estimation of the number of beneficiaries of hydrologic ES (and by extension, the magnitude of total benefits). By simply running a full interaction of the precipitation and population datasets they show that the population predicted to experience various levels of runoff varies tremendously in magnitude and even sign (see Fig. 7 of their paper). This analysis provides an important cautionary note while demonstrating that significant insights can be gained from relatively straightforward UA workflows (even if they require some effort to acquire inputs). We suggest it makes a good case for going beyond individual parameter exploration to engage in routine consideration of multiple spatial input layers in ES modeling studies.

2.2.3. Processes and methods that facilitate uncertainty assessment help build understanding in other ways

Importantly, the modeling frameworks and workflows set up to enable UA often provide other insights in the process. In the analysis of Huber et al. above, the meta-regression structure not only helps provide uncertainty ranges for benefits transfer estimates, but also identifies important contextual information for interpreting evidence. In their case, they show how an interesting outlier result related to Alaskan game values is also associated with studies sharing one particular methodological feature: To put them into a comparable unit of analysis for the meta-regression (value per day), they required converting from the "natural" units (i.e., the units each study was originally conducted in) to the per-day values, a step where conceptual error or invalid adjustment may be introduced. Decision-makers can bring this contextual information into other unmodeled contexts to inform their decisions, and researchers can use it to identify where additional study would have highest value.

Along the same theme, in their extensive numerical sensitivity analysis mentioned above, Morzaria-Luna et al. not only identify significant ranges on potential fish provisioning levels, but they also determine sensitivities, as well as conditions under which performance of the emulator requires greater attention to ensure correct interpretation in light of model instabilities.

Lastly, Maldonado et al. (2018, this issue) blend participatory methods that aim to capture cultural concerns as well as more

[4] https://www.susdrain.org/resources/best.html.

concretely-defined biophysical services in Andalusia, Spain. In the development of the Object-Oriented Bayesian Network (OOBN) describing the socio-ecological system, they demonstrate the elicitation, aggregation, and structuring of the complex relationships by which drivers of landscape condition affect outcomes of interest. This transparency is valuable in and of itself, with the identification and sharing of model structure facilitating participation and representation of diverse concerns and actions (Landuyt et al., 2013). This is in addition to the direct value of the OOBN in helping propagate the impact of scenarios in a more formal yet feasible manner, one which avoids reliance on data-intensive process-based modeling and formal valuation frameworks, yet is also able to incorporate information from those more traditional frameworks when available.

3. Discussion: considering the special issue in the broader context of promoting uncertainty assessment

Overall, we were pleased by the range of methods and utility of UA demonstrated in the articles within this issue. At the same time, it is important to critically reflect on the extent to which such a collection can help address the overall problem of inadequate attention to uncertainty, and also consider additional issues raised by the papers themselves. We begin with the latter, and then zoom out to consider the bigger picture challenges of promoting context-appropriate uncertainty assessment.

3.1. "Transparent and feasible" does not imply "low-capacity" or "low-effort"

While showing that uncertainty assessment can usefully be conducted in a variety of contexts, the articles in this special issue raise a number of challenges that might face an ES practitioner attempting to implement good UA practice. In some cases, these are tied specifically to the uncertainty assessment approach used, but some stem from the use of modeling approaches that facilitate consideration of ES.

Many of these are simply related to effort: For example, the outranking approach demonstrated by Martin and Mazzotta (2018b) helps directly consider strengths of evidence in decision-maker beliefs, but ultimately still relies on transforming beliefs into quantitative functional forms and parameters. The elicitation requires non-trivial engagement efforts, and structural and parametric uncertainty present in the value structures may require yet more sensitivity analysis to be included within the workflow. Similarly, by identifying that the rules for translating narrative scenarios to land cover are a primary driver of scenario ES outcomes, Harmackova and Vackar highlight that stakeholder engagement, vetting, and uncertainty communication may need to focus on key intermediate steps, potentially adding effort to the engagement process.

Second, the quantitative methods utilized by a majority of the papers – from Bayesian analyses (Maldonado et al., Willcock et al.) to numerical uncertainty propagation (Vauhkonen and Packalen, Ashley et al., Morzaria Luna et al.), to Monte Carlo assessment to sensitivity analyses (Monge et al., van Soesbergen and Mulligan) – are recognized within their subfields as requiring special knowledge and detailed attention. For example, Bayesian networks require expert judgment or additional testing to determine appropriate discretizations of continuous variables, while complex uncertainty propagation in integrated models may require time and computing skills beyond the toolkit of the typical ES analyst. This is, of course, not an insurmountable barrier, but one that does require appropriate resources.

Third, while ES modeling tools that include "built-in" uncertainty assessment (such as those described in Ashley et al., Huber et al., Willcock et al.) facilitate uptake, without careful interface design they may allow an analyst to think they have *treated* uncertainty without necessarily having carefully *engaged* with it and its implications. In particular, built-in uncertainty assessments tend to focus on parameter uncertainty and in so doing they may reduce the likelihood users consider structural and contextual uncertainty factors, as these are harder to include in an interface. Interfaces (such as B£ST) that guide a user to consider sources of uncertainty by requiring some active user input may go some way to mitigating this problem. However, the challenges are particularly acute in the realm of integrated models, where true insight comes from considering the dynamics of individual components and their interaction. In these cases it is difficult to extract that insight by applying semi-automated approaches that treat the integrated model simply as a single entity translating inputs to outputs.

3.2. How can the ES community help?

In addition to calling for demonstration of success stories, the workshop that motivated this special issue identified a broad range of challenges to promoting wider adoption of UA, with implications for how various actors in the ES realm can work to address them. Below we present a combination of recommendations for the ES community that emerged from the workshop, and from reflections on our diverse experience with ES and with the special issue process itself.

3.2.1. Continue lowering the burden of uncertainty assessment

Programming skill does not go hand in hand with an interest in uncertainty assessment. In our own work we have heard from model users that user interfaces that help easily explore scenarios and parametric uncertainty would be highly valuable. These users see the value of uncertainty assessment, but for some of them it really is "too hard" to conduct it (Bryant and Hamel, 2017). Good progress is being made on this front by developers of ES software, with Huber et al. and Ashley et al. providing custom tools with built-in uncertainty considerations. Willcock et al. (2018, this issue) demonstrate how the broader ARIES modeling architecture[5] allows ES assessment within a Bayesian framework and therefore provides uncertainty assessments with no additional effort beyond that required for the modeling itself. WaterWorld,[6] used in van Soesbergen and Mulligan (2018, this issue), contains a built-in scenario tool (Mulligan et al., 2015). New products from the Natural Capital Project complement InVEST on this front as well: MESH[7] eases the task of multi-scenario, multi-service assessment by providing an integrated interface in which to conduct them, while the multi-objective spatial prioritization tool ROOT[8] automatically provides a visual assessment of how robust results are to uncertainty in weights on different ecosystem service objectives.

Providing guidance on the treatment of specific sources of uncertainty can also help. For example, Mandle et al. (2016) assembled guidance on how climate change considerations enter into InVEST model inputs and where modelers can find key inputs, reducing the effort for a user who wants to consider climate change uncertainty but does not have a good grounding with which to begin the process. Similar efforts could be made for drivers like population and land use change.

3.2.2. Embrace the use of multiple models even for single ecosystem services

The above enhancements are certainly welcome and we hope will usefully advance UA in the ES realm. However, by default they mainly facilitate parametric and scenario uncertainty, leaving structural uncertainty untouched in the absence of conscious effort by savvy users. This is not the norm in other disciplines. For example, climate modeling has utilized multiple models (sometimes known as ensemble modeling) for quite some time (e.g., Murphy et al., 2004). Schulp et al. (2014) conducted a comparison of ecosystem service mapping approaches, but

[5] http://aries.integratedmodelling.org/.
[6] http://www.policysupport.org/waterworld.
[7] https://www.naturalcapitalproject.org/mesh/.
[8] https://www.naturalcapitalproject.org/root/.

this was for scholastic purposes, and the approach has not diffused into common ES practice. Therefore, modelers and those demanding ES results can advocate for the consideration of multiple models to address the same service or overlapping services. While platforms to facilitate ensemble modeling can help immensely in realizing this goal, they are not critical: Even in the absence of an integrated platform, some models are low effort to run because they come with pre-populated data (e.g., WaterWorld), while other models share many inputs across each other, in effect requiring diminishing levels of effort to run additional models beyond the first.

3.3.3. Where using multiple models is not feasible, avoid relying on a default model

Building expertise on a particular model is an investment, and it is understandable that analysts would wish to capitalize on that investment by applying models that are familiar to them. Nevertheless ES analysts must strive to avoid treating every ecosystem services question as a nail suitable for their hammer. For consulting firms and NGOs this may mean keeping diverse skill sets on staff or on retainer; for academic collaborations it might mean budgeting changes and openness to bringing in outside expertise from different "camps" – whether on contract or via informal collaboration. Regardless of the ultimate models chosen for a particular effort, the act of deliberating on model selection benefits uncertainty assessment by creating awareness of model features that require attention (e.g., resolution in time versus space).

3.3.4. Deliberately assess the value of UA and communicate successes

The SESYNC workshop identified a lack of obvious cases where uncertainty assessment mattered as one reason for less-than-desirable uptake of UA. This special issue is a first step in that direction, but applies a looser criteria for impact than may be compelling to some. While we focus on how conducting UA provides *potential* benefits, whether those benefits are truly capitalized on in decision contexts is demonstrated by only a few articles in our issue. However, demonstrating the use of knowledge in decision making is generally a challenging prospect – indeed, it is difficult enough to show instrumental use of ecosystem services information in real decision processes (McKenzie et al., 2014) without the added challenge of demonstrating how uncertainty framing plays a role. Efforts to assess the impact of ecosystem services knowledge should continue and give attention to the role of uncertainty. However, given that showing the impact of providing quantitative ES information is a precondition for showing that formal uncertainty assessment matters, and that even this first step remains a research frontier, ES analysts should be open to pluralistic forms of evidence on this topic. Evidence of demand for uncertainty information is certainly helpful in this regard (as provided by Willcock et al. (2016) and Willcock et al. (2018, this issue)).

3.3.5. Learn lessons from other disciplines – not just techniques

Hamel and Bryant (2017) argued that many challenges to conducting uncertainty assessment were addressed in the practices adopted by other disciplines, and our comments above on the importance of multi-model approaches echo that theme. However, the relevance of other disciplines also applies to "lessons learned" and evidence generated about the value of uncertainty analysis in affecting decisions. While our own anecdotal experience suggests that ES practitioners find ES-specific examples most compelling, an efficient path may lie in compiling examples of the value of uncertainty assessment across integrated modeling applications, and carefully packaging those lessons specifically for ES practitioners. Evidence from other methods-oriented fields like risk analysis (Morgan and Henrion, 1990), structured decision making (Gregory et al., 2012), and decision making under deep uncertainty (Maier et al., 2016) can help as well. None of the papers included in this special issue, for example, were explicitly focused on identifying robust policies in the face of uncertainty – efforts to do so would presumably more frequently lead to cases where consideration of uncertainty changes decisions.

3.3.6. Use transparency to promote "model thinking" and shared understanding of the goals of UA

Ultimately, applied ES assessments engage people with very different backgrounds: Stakeholders of course may come with a variety of perspectives, and even the project team may hold diverse competencies and interests. These differences mean that the individuals involved may have very different perceptions of UA. Furthermore, given that ES modeling efforts are generally embedded in more complex systems (Clark et al., 2016), no analysis will be able to comprehensively consider all uncertainties. It is therefore important that the project manager or key analysts work to bridge the gaps in understanding by facilitating a process for co-determining those uncertainties that are most likely to matter.

We believe that promoting a goal-oriented approach starting with – and continually revisiting – why ES analysis is being conducted can help. In this broad sense, UA then takes the form of examining the relationship between assumptions in the modeling process relative to the ability to inform the goals of the ES analysis. In a transparent process of knowledge co-production, decision-makers can be encouraged to poke holes in analyses that may need to be improved. Conversely, sometimes this means that formalized uncertainty assessment may not actually be necessary. For example, Martin and Mazzotta (this issue) note that, based on their close engagement in a facilitated process of knowledge co-production, the decision-makers "were comfortable defending" there preference representations as they stood, so that a sensitivity analysis of the parameters in the outranking method was not deemed necessary. We agree that transparency in process and results is key and may often substitute for quantitative uncertainty assessment. However, some – at least qualitative – attention to sources of uncertainty and their potential impact on conclusions is, almost by definition, a necessary element of transparency.

4. Conclusion

Challenges remain in determining the most appropriate ways to conduct uncertainty assessment in applied ES modeling efforts, and in promoting the adoption of those methods. To address some of these challenges, this special issue provides a consolidated set of examples that ES analysts can follow to understand how to conduct many different forms of uncertainty assessment, and why conducting it adds value to the modeling process. Importantly, while some uncertainty assessment does change recommended decisions or policy actions, we show that uncertainty assessment has benefits even when it does not cause such changes. Specifically, it can contribute new understanding of the focal system, contribute new understanding regarding the nature of available evidence, and allow decision-makers to assess the value of new information or whether the level of confidence they can place in the modeling results is adequate with respect to the decision at hand.

Ecosystem services assessment is, and will remain, a fundamentally multidisciplinary endeavor. Other arguably less integrative disciplines have been able to converge around commonly accepted standards for modeling practice, and some have called for such standards in ES (e.g., Polasky et al., 2015), noting they have yet to take hold within the ES realm. We agree that more clear expectations about what successful UA looks like – or at least guidelines to avoid common pitfalls – can be helpful. However, the multidisciplinary nature of ES may preclude clear cut standards that will effectively speak to the diversity of applications that fall under the ES banner, and the variation in prominence that different disciplines will have in each application. Therefore, those who practice in the ES realm need to be aware of appropriate techniques across multiple disciplines and their relevance to the decision-making contexts in which they work. The articles in this issue demonstrate that, notwithstanding the challenges, a combination of awareness, time, and attention can go a long way towards producing decision-relevant insights through transparent and feasible uncertainty assessment.

Acknowledgments

We would like to thank SESYNC for funding the November 2016 workshop that motivated this special issue, and the other participants at that workshop who represented academic and practitioner considerations: Ken Bagstad, Nirmal Bhagabati, Jae Chung, Tony Jakeman, Diana Lane, Michele Lim, Doug Lipton, Eric Lonsdorf, JuanSe Lozano, Guillermo Mendoza, Lydia Olander, Stephen Posner, Jefferson Valencia. We would also like to thank three anonymous reviewers and several informal reviewers of this paper, and the authors and reviewers of the included articles for their diligent work to ensure those papers met the additional the criteria for our special issue.

Funding

Benjamin Bryant was supported by the Ishiyama Foundation and the Marianne and Marcus Wallenberg Foundation. Perrine Hamel was supported by the Marianne and Marcus Wallenberg Foundation.

References

Ashley, R., Gersonius, B., Digman, C., Horton, B., Smith, B., Shaffer, P., 2018. Including uncertainty in valuing blue and green infrastructure for stormwater management. Ecosyst. Serv. 33 (Part B).

Bagstad, K.J., Cohen, E., Ancona, Z.H., McNulty, S.G., Sun, G., 2018. The sensitivity of ecosystem service models to choices of input data and spatial resolution. Appl. Geogr. 93, 25–36. https://doi.org/10.1016/j.apgeog.2018.02.005.

Baustert, P., Othoniel, B., Rugani, B., Leopold, U., 2018. Uncertainty analysis in integrated environmental models for ecosystem service assessments: Frameworks, challenges and gaps. Ecosyst. Serv. 33 (Part B).

Bennett, N.D., Croke, B.F.W., Guariso, G., Guillaume, J.H.A., Hamilton, S.H., Jakeman, A.J., et al., 2013. Characterising performance of environmental models. Environ. Modell. Software 40, 1–20. https://doi.org/10.1016/J.ENVSOFT.2012.09.011.

Bryant, B. P., Hamel, P., 2017. Motivating and improving uncertainty assessment in ecosystem services modeling to inform decisions: Workshop report. https://doi.org/10.25936/629t-bx79.

Clark, W.C., van Kerkhoff, L., Lebel, L., Gallopin, G.C., 2016. Crafting usable knowledge for sustainable development. Proc. Natl. Acad. Sci. 113 (17), 4570–4578. https://doi.org/10.1073/pnas.1601266113.

Gregory, R., Failing, L., Harstone, M., Long, G., McDaniels, T., Ohlson, D., 2012. Structured Decision Making: A Practical Guide to Environmental Management Choices. Wiley-Blackwell.

Guillaume, J.H.A., Helgeson, C., Elsawah, S., Jakeman, A.J., Kummu, M., 2017. Toward best practice framing of uncertainty in scientific publications: a review of water resources research abstracts. Water Resour. Res. 53 (8), 6744–6762. https://doi.org/10.1002/2017WR020609.

Hamel, P., Bryant, B.P., 2017. Uncertainty assessment in ecosystem services analyses: seven challenges and practical responses. Ecosyst. Serv. 24, 1–15. https://doi.org/10.1016/j.ecoser.2016.12.008.

Harmáčková, Z.V., Vačkář, D., 2018. Future uncertainty in scenarios of ecosystem services provision: linking differences among narratives and outcomes. Ecosyst. Serv. 33 (Part B).

Hou, Y., Burkhard, B., Müller, F., 2013. Uncertainties in landscape analysis and ecosystem service assessment. J. Environ. Manage. 127, S117–S131. https://doi.org/10.1016/j.jenvman.2012.12.002.

Huber, C., Meldrum, J., Richardson, L., 2018. Improving confidence by embracing uncertainty: a meta-analysis of U.S. hunting values for benefit transfer. Ecosyst. Serv. 33 (Part B).

Landuyt, D., Broekx, S., D'hondt, R., Engelen, G., Aertsens, J., Goethals, P.L.M., 2013. A review of Bayesian belief networks in ecosystem service modelling. Environ. Modell. Software 46, 1–11 Retrieved from https://www.sciencedirect.com/science/article/pii/S1364815213000741.

Lavorel, S., Bayer, A., Bondeau, A., Lautenbach, S., Ruiz-Frau, A., Schulp, N., Seppelt, R., Verburg, P., van Teeffelen, A., Vannier, C., Arneth, A., Cramer, W., Marba, N., 2017. Pathways to bridge the biophysical realism gap in ecosystem services mapping approaches. Ecol. Indic. 74, 241–260. https://doi.org/10.1016/J.ECOLIND.2016.11.015.

Maier, H.R., Guillaume, J.H.A., van Delden, H., Riddell, G.A., Haasnoot, M., Kwakkel, J.H., 2016. An uncertain future, deep uncertainty, scenarios, robustness and adaptation: how do they fit together? Environ. Modell. Software 81, 154–164. https://doi.org/10.1016/j.envsoft.2016.03.014.

Maldonado, A.D., Aguilera, P.A., Salmerón, A., Nicholson, A.E., 2018. Probabilistic modeling of the relationship between socioeconomy and ecosystem services in cultural landscapes. Ecosyst. Serv. 33 (Part B) Retrieved from https://www.sciencedirect.com/science/article/pii/S2212041617306745.

Mandle, L., Vogl, A.L., Hamel, P., Silver, J.M., Griffin, R., Wood, S.A., et al., 2016. Incorporating climate change scenarios into InVEST and RIOS. Retrieved from: https://www.naturalcapitalproject.org/wp-content/uploads/2016/02/Incorporating-climate-change-scenarios-into-InVEST-and-RIOS-2016-01-11.pdf.

Martin, D., Mazzotta, M., 2018b. Non-monetary valuation using Multi-Criteria Decision Analysis: using a strength-of-evidence approach to inform choices among alternatives. Ecosyst. Serv. 33 (Part B).

Martin, D.M., Mazzotta, M., 2018a. Non-monetary valuation using Multi-Criteria Decision Analysis: sensitivity of additive aggregation methods to scaling and compensation assumptions. Ecosyst. Serv. 29, 13–22. https://doi.org/10.1016/J.ECOSER.2017.10.022.

McKenzie, E., Posner, S., Tillmann, P., Bernhardt, J.R., Howard, K., Rosenthal, A., 2014. Understanding the use of ecosystem service knowledge in decision making: Lessons from international experiences of spatial planning. Environ. Plann. C: Govt. Policy 32 (2), 320–340. https://doi.org/10.1068/c12292j.

Merritt, W.S., Fu, B., Ticehurst, J.L., El Sawah, S., Vigiak, O., Roberts, A.M., et al., 2017. Realizing modelling outcomes: a synthesis of success factors and their use in a retrospective analysis of 15 Australian water resource projects. Environ. Modell. Software 94, 63–72. https://doi.org/10.1016/j.envsoft.2017.03.021.

Monge, J., Daigneault, A., Dowling, L., Harrison, D.R., Awatere, S., Ausseil, A., 2018. Implications of future climatic uncertainty on payments for forest ecosystem services: the case of the East Coast of New Zealand. Ecosyst. Serv. 33 (Part B). https://doi.org/10.1016/j.ecoser.2018.04.010.

Morgan, M.G., Henrion, M., 1990. Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis. Cambridge University Press, Cambridge.

Morzaria-Luna, H.N., Ainsworthc, C.H., Tarnecki, J.H., Grüss, A., 2018. Diet composition uncertainty determines impacts on fisheries following an oil spill. Ecosyst. Serv. 33 (Part B). https://doi.org/10.1016/j.ecoser.2018.05.002.

Mulligan, M., Benítez-Ponce, S., Lozano-V, J.S., Sarmiento, J.L., 2015. Policy support systems for the development of benefit-sharing mechanisms for water-related ecosystem services. In: Martin-Ortega, J., Ferrier, R.C., Gordon, I.J., Khan, S. (Eds.), Water Ecosystem Services. Cambridge University Press, Cambridge, pp. 99–109. https://doi.org/10.1017/CBO9781316178904.013.

Murphy, J.M., Sexton, D.M.H., Barnett, D.N., Jones, G.S., Webb, M.J., Collins, M., Stainforth, D.A., 2004. Quantification of modelling uncertainties in a large ensemble of climate change simulations. Nature 430 (7001), 768–772. https://doi.org/10.1038/nature02771.

Ochoa, V., Urbina-Cardona, N., 2017. Tools for spatially modeling ecosystem services: Publication trends, conceptual reflections and future challenges. Ecosyst. Serv. 26, 155–169. https://doi.org/10.1016/j.ecoser.2017.06.011.

Polasky, S., Tallis, H., Reyers, B., 2015. Setting the bar: standards for ecosystem services. PNAS 112 (24), 7356–7361. https://doi.org/10.1073/pnas.1406490112.

Refsgaard, J.C., van der Sluijs, J.P., Højberg, A.L., Vanrolleghem, P.A., 2007. Uncertainty in the environmental modelling process – A framework and guidance. Environ. Modell. Software 22 (11), 1543–1556. https://doi.org/10.1016/j.envsoft.2007.02.004.

Santos de Lima, L., Krueger, T., García-Marquez, J., 2017. Uncertainties in demonstrating environmental benefits of payments for ecosystem services. Ecosys. Serv. 27, 139–149. https://doi.org/10.1016/j.ecoser.2017.09.005.

Schulp, C.J.E., Burkhard, B., Maes, J., Van Vliet, J., Verburg, P.H., 2014. Uncertainties in ecosystem service maps: A comparison on the european scale. PLoS ONE 9 (10), e109643. https://doi.org/10.1371/journal.pone.0109643.

Seppelt, R., Dormann, C.F., Eppink, F.V., Lautenbach, S., Schmidt, S., 2011. A quantitative review of ecosystem service studies: approaches, shortcomings and the road ahead. J. Appl. Ecol. 48 (3), 630–636. https://doi.org/10.1111/j.1365-2664.2010.01952.x.

Uusitalo, L., Lehikoinen, A., Helle, I., Myrberg, K., 2015. An overview of methods to evaluate uncertainty of deterministic models in decision support. Environ. Modell. Software 63, 24–31. https://doi.org/10.1016/j.envsoft.2014.09.017.

van Soesbergen, A., Mulligan, M., 2018. Uncertainty in data for hydrological ecosystem services modelling: Potential implications for estimating services and beneficiaries for the CAZ, Madagascar. Ecosyst. Serv. 33 (Part B).

Vauhkonen, J., Packalen, T., 2018. Uncertainties related to climate change and forest management with implications on climate regulation in Finland. Ecosyst. Serv. 33 (Part B) Retrieved from https://www.sciencedirect.com/science/article/pii/S2212041617306617.

Walker, W.E., Harremoës, P., Rotmans, J., van der Sluijs, J.P., van Asselt, M.B.A., Janssen, P., Krayer von Krauss, M.P., 2003. Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support. Integr. Assess. 4 (1), 5–17. https://doi.org/10.1076/iaij.4.1.5.16466.

Warmink, J.J., Janssen, J.A.E.B., Booij, M.J., Krol, M.S., 2010. Identification and classification of uncertainties in the application of environmental models. Environ. Modell. Softw. 25 (12), 1518–1527. https://doi.org/10.1016/j.envsoft.2010.04.011.

Willcock, S., Hooftman, D., Sitas, N., O'Farrell, P., Hudson, M.D., Reyers, B., Bullock, J.M., 2016. Do ecosystem service maps and models meet stakeholders' needs? A preliminary survey across sub-Saharan Africa. Ecosyst. Serv. 18, 110–117. https://doi.org/10.1016/J.ECOSER.2016.02.038.

Willcock, S., Martínez-López, J., Hooftman, D.A.P., Bagstad, K.J., Balbi, S., Marzo, A., et al., 2018. Machine learning for ecosystem services. Ecosyst. Serv. 33 (Part B). https://doi.org/10.1016/j.ecoser.2018.04.004.