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Review

Identifying uncertainties in scenarios and models of socio-ecological systems in support of decision-making

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https://doi.org/10.1016/j.oneear.2021.06.003

SUMMARY

There are many sources of uncertainty in scenarios and models of socio-ecological systems, and understanding these uncertainties is critical in supporting informed decision-making about the management of natural resources. Here, we review uncertainty across the steps needed to create socio-ecological scenarios, from narrative storylines to the representation of human and biological processes in models and the estimation of scenario and model parameters. We find that socio-ecological scenarios and models would benefit from moving away from "stylized" approaches that do not consider a wide range of direct drivers and their dependency on indirect drivers. Indeed, a greater focus on the social phenomena is fundamental in understanding the functioning of nature on a human-dominated planet. There is no panacea for dealing with uncertainty, but several approaches to evaluating uncertainty are still not routinely applied in scenario modeling, and this is becoming increasingly unacceptable. However, it is important to avoid uncertainties becoming an excuse for inaction in decision-making when facing environmental challenges.

INTRODUCTION

"The whole problem with the world is that fools and fanatics are always so certain of themselves, but wiser people so full of doubts."[1] With this phrase, Bertrand Russell highlights the imperative of embracing uncertainty rather than fooling ourselves into thinking that it does not exist. This holds especially true for how we understand the natural world, including the increasingly important role of humans in socio-ecological systems. We know that socio-ecological systems are complex. They are non-linear, bifurcate, and have feedbacks and tipping points, all of which makes their future development inherently uncertain and difficult to predict. Indeed, the future is a place we can never know; we cannot observe it, and we cannot measure it. Yet, decision-makers are challenged with planning short- to long-term strategies for preserving biodiversity and the contributions of nature to people[2] and, so, we need to anticipate what the future may hold.

The scientific response to this challenge has been the development of scenarios to explore the uncertainty space of plausible, but unknown, futures.[3] Scenarios are not predictions, but are "a plausible and often simplified description of how the future may develop based on a coherent and internally consistent set of assumptions about key driving forces and relationships."[4] Scenarios are commonly underpinned by qualitative descriptions (narrative storylines) of the underlying direct and indirect drivers of change, including policy options,[3,5] which are often translated into impacts on biodiversity, ecosystem services, and complex socio-ecological systems using models in a storyline and simulation approach.[3] Hence, scenarios can be qualitative, quantitative, or both. As such, scenarios and models are invaluable tools in guiding long-term, strategic policies that prompt management actions and increase public awareness of the future threats to nature.[6]

Due to the complexity of socio-ecological systems, but also to advances in knowledge and observation capacity, models are being developed with increasing complexity, involving many processes and feedbacks, and integrating multiple components of the ecosystem, from the physical environment to human societies. Examples include, land-use models,[7] agent-based models,[8] marine ecosystem models,[9,10] models of trophic levels,[11] dynamic vegetation models,[12,13] state and transition landscape models,[14] and niche-based models of species response to climate and land-use change.[15] There has been a strong focus on developing comprehensive modeling tools from empirical evidence,[16,17] but, until now, far less effort has been dedicated to exploring the uncertainties within these models, especially when used to quantify scenarios.

Identifying and quantifying future uncertainties may be key in achieving buy-in from stakeholders, to prompt evidence-based decision-making, and to shift mindsets on the perception of the future threats to biodiversity, ecosystems, and ecosystem services. To increase the influence of scenario and modeling analyses on policy and to trigger appropriate management responses, the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) has strongly encouraged the use of scenarios and models, but warns that these "should be applied with care, taking into account uncertainties and unpredictability associated with model-based projections."[3] A critical challenge for improving scenarios and models of socio-ecological systems is to augment the scientific capacity in quantifying the uncertainty within and among model projections.[18]

Here, we review the current state of knowledge about the uncertainties associated with scenarios and models of socio-ecological systems within the context of decision-making, by which we mean the policy decisions made within private or public sector organizations. In doing so, we seek to address some of the key challenges raised by Elsawah et al.[19] that relate to uncertainty, such as the role of stakeholder engagement in the co-development of scenarios, linking scenarios across multiple geographical, sectoral, and temporal scales, improving the links between qualitative and quantitative scenarios, addressing surprises, addressing scenario consistency, communicating scenarios, and linking scenarios to decision-making. We do not aim to undertake an exhaustive evaluation of scenarios and model types. Instead, we use examples from a very wide range of scenarios and models to illustrate a comprehensive review of sources of uncertainty. A comprehensive review of sources of uncertainty in scenarios and models does not require a comprehensive review of scenarios and models. A wider ranging review can be found in the IPBES[3] assessment of scenarios and models.

We provide an overview of how uncertainty is treated within socio-ecological systems analysis and how understanding these uncertainties can enhance confidence in the creation of the next generation of scenarios and models. This is novel in both tackling a comprehensive review of sources of uncertainty in scenarios and models, exploring the implications of these uncertainties for decision-making and in setting out a number of potential solutions and recommendations for how to deal with these uncertainties.

TYPES OF UNCERTAINTIES

We focus on three categories of uncertainty: scenario uncertainty, model uncertainty, and decision-making uncertainty (see Table 1) across terrestrial and marine realms. We explore the whole chain of steps needed to create socio-ecological scenarios and models that are useful for decision-makers, from narrative storylines, the representation of human and biological processes in models, the estimation of model parameters, and model initialization and evaluation. Some of these sources of uncertainty relate to differences in worldviews, some to the limits of our current knowledge and others to our capacity to represent processes within models, including the reliability of model input data across spatial and temporal scales. Figure 1 shows the types of uncertainty (from Table 1) in the steps from observational data, model development, the construction of qualitative storylines and quantitative scenario projections that together provide input to decision-making.

SCENARIO UNCERTAINTY

Linguistic uncertainty

Linguistic uncertainty has been classified into five distinct types: vagueness, context dependence, ambiguity, indeterminacy of theoretical terms, and under-specificity.[20] Of these, ambiguity and vagueness arguably occur most commonly, largely because scenario terminology is often based on common language words. Indeed, the word "scenario" itself derives from the language of the theater. Yet, different communities can sometimes attribute different meanings to the same "precise" word, i.e., their use is ambiguous. For example, the word "pathways" is used as a synonym for "projections" or "trajectories" (as in the shared socio-economic pathways),[21] or alternatively it is used to describe a set of time-dependent actions that are required to achieve a future vision.[2] Using the term in one sense can lead to confusion if it is interpreted as being used in the other sense. Vagueness relates to statements with insufficient precision. For example, "population growth will increase strongly over the coming 50 years" tells us nothing about what a strong population growth actually looks like. Is it a doubling of population, or tripling, or something else? These different types of linguistic uncertainty commonly occur in narrative storylines, and they are especially important considerations when communicating the outcomes of scenario processes to decision-makers. Recent development of information technology provides a means to minimize linguistic uncertainty by building ontologies, i.e., an ensemble of formal definitions of concepts and their relationships within the domain of interest, and their synonyms or equivalents in closely related domains. While domain-specific ontologies exist in ecology that facilitate data mining and sharing,[22] to our knowledge, there is no widely accessible controlled vocabulary or thesaurus standardizing the meaning of the basic concepts used in scenarios of socio-ecological systems, as is the case with ontologies related to the Intergovernmental Panel on Climate Change (IPCC).[23]

Table 1. Sources of uncertainty and their description in scenarios and models of socio-ecological systems

Uncertainty sources	Description	Uncertainty types
Scenario uncertainty	The qualitative description of alternative worldviews and their development into the future and the quantification of model input parameters that are conditional on these descriptions.	*Linguistic uncertainty*. The use of similar terms to mean different things in different research communities, e.g., pathways, ensembles, boundary conditions. *Narratives storyline uncertainty*. The limits to imagining unknown futures (e.g., unknown unknowns). This can relate, for example, to alternative worldviews or the uncertainties associated with participatory processes arising from internal consistency and knowledge limitations. *Scenario parameter uncertainty*. The estimation of quantitative parameters from narrative storylines that are subsequently used in models. Scenario parameter uncertainty follows from the interpretation of quantitative values from qualitative narratives, e.g., the number of people in a "high population growth" scenario.
Model uncertainty	The representation of processes in models and how this is done.	*Structural (epistemic) uncertainty*. The uncertainties associated with the choice and the representation of processes in models. *Input data uncertainties*. The variability in baseline data conditions that are used to initialize a model, including thematic classification, i.e., how classes are defined in, for example, land-use maps. *Error propagation uncertainty*. The amplification (or dampening) of the transmission of errors across multiple coupled models. The role of meta-modeling and indirect effects (such as cross-sectoral interactions).
Decision uncertainty	Communicating and translating the results of scenario and modeling studies into decision-making.	*Data interpretation for decision-making*. Selective use of data or information from different sources and their interpretation. *Analyzing at relevant spatiotemporal scales*. The selection of spatiotemporal scales at which simulated data are analyzed, and the granularity of derived indicators (e.g., level of integration across biodiversity facets, merging subsets of ecosystem services). *Decision-making tools*. The variety of decision-supporting methods, e.g., multi-criteria decision analysis.

Narratives storyline uncertainty

The first step in the construction of scenarios is often the development of qualitative, narrative storylines.[5] These describe alternative trajectories in the key drivers of change (and their interactions) with a focus on socio-economic change. Socio-economic trajectories can also be associated with changes in physical conditions, such as climate change, where a change in climate is assumed to be internally consistent with drivers of, for example, societal consumption patterns and industrialization.[24] The uncertainties associated with the development of narrative storylines arise from how to create this internal consistency using mental models,[25] as well as the difficulty of imagining futures for which there are no historical analogs and representing a sufficient range of possible futures.[26,27] This affects the "plausibility" of narrative storylines in terms of whether the assumed causal relationships reflect real-world development, or the worldviews of the storyline developer. A particular case of this problem are "black swans," which reflect shocks or surprises to a system, i.e., events that are unexpected or assumed to have a low probability of occurring, but which have a high impact.[28] Black swans by their very nature can be difficult to anticipate or imagine, and are often unprecedented historically. The most appropriate way of dealing with uncertainties in storyline development is to clearly state and document the assumptions that underpin a narrative, and to communicate these assumptions when reporting a scenario study.[29]

Most narrative storylines focus on the supply side of natural resource systems (e.g., crop production or fish harvesting), and say little about the demand side (e.g., consumption patterns, such as dietary preferences) or the economic and institutional transformations that implicitly underlie the storylines. Although many "stylized" scenarios exist for diets, e.g., what would be the consequences for biodiversity of people becoming vegetarian or vegan,[30,31] these do not account for the transitions from where we are today to this assumed future situation.[32] Hence, the uncertainties associated with these transitions are not explicit.

Existing storylines of marine ecosystems largely focus on a narrow set of direct drivers, such as fishing or climate change,[33] or short-term policy interventions (such as protected areas or

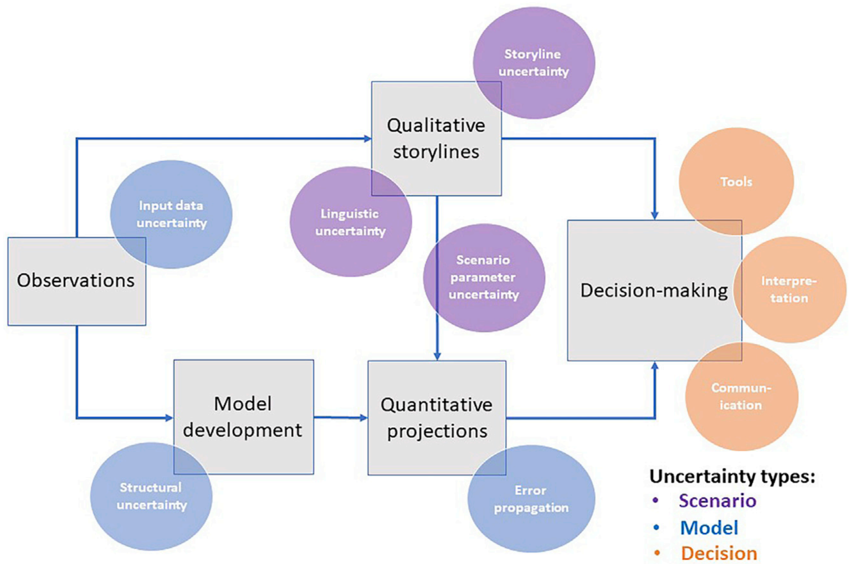

Figure 1. Sources of uncertainty in scenarios and models of socio-ecological systems within the context of decision-making
The circled sources of uncertainty are addressed in the main text: purple refers to scenario uncertainty, blue to model uncertainty, and orange to decision uncertainty.

management of fishing effort). Moreover, the consideration of indirect drivers, such as seafood demand from changes in population, consumption patterns or international trade, are not explicit in most marine storylines. Recent studies increasingly focus on expanding the scope of uncertainties by developing storylines that consider multiple drivers and policy interventions, in particular the interactions between climate change, fishing, and management.[34–36]

Terrestrial studies have a longer tradition of evaluating multiple, often cross-scale drivers in developing narrative storylines.[37] However, uncertainties arise from an overreliance on climate change as a driver, and not accounting for other drivers that are critical for socio-ecological systems, such as invasive alien species, trade in wild species, or air and water pollution.[2] Furthermore, uncertainties also arise from failure to account for indirect, cross-sectoral interactions.[37]

Participatory approaches, by which narrative storylines are co-created with stakeholders, add richness and diversity to storyline development, and strengthen the link between storylines and scenario quantification with models,[38] but are highly dependent on the selection of individual stakeholders and the extent of their explicit and tacit knowledge. Stakeholder mapping exercises[38] that seek to maximize stakeholder diversity are one way of resolving this problem. Participatory approaches are well developed in the marine realm, especially in fisheries management and marine spatial planning.[39,40]

Scenario parameter uncertainty

Simulation models can quantify the outcomes of narrative storylines for specific indicators. This requires the translation of the qualitative statements within a storyline into quantitative model inputs, which in itself has potential to introduce additional uncertainties.[5] We draw a distinction here between "scenario parameter uncertainty" and "model parameter uncertainty." Scenario parameter uncertainty derives from the translation of qualitative narratives into quantitative values, and so is dependent on the scenario itself, i.e., the quantitative values vary across scenarios. For example, a scenario parameter could be the number of people in a high, medium, or low population growth storyline. In general, scenario parameters relate to the socio-economic components of socio-ecological systems and may themselves be model inputs. Model parameter uncertainty refers to the estimation of parameters within the functions that represent modeled processes, e.g., a rate constant or capacity, and often, but not always, relate to the biophysical components of socio-ecological systems. Hence, model parameter uncertainty depends on the system and the model of that system, and is independent of a scenario. Scenario parameter quantification often uses best-guess estimates that sometimes draw on uncertain, historical analogs. However, the majority of these studies do not account for the uncertainties associated with the process of estimating scenario parameters themselves. A few exceptions to this have defined "credible" parameter ranges,[41] or have used conditional probabilistic futures methods.[42]

In the conditional probabilistic approach, probability distribution functions (PDFs) are created for the scenario parameters that are conditional on the assumptions within a scenario storyline, thus reflecting the uncertainty range in the estimation of a scenario parameter.[42–44] When combined with Monte Carlo sampling across the PDFs and multiple model simulations this approach is able to explore the range of scenario outcomes that are contingent on the uncertainties of scenario parameter inputs, although subjective assumptions and choices made in Monte Carlo sampling can introduce uncertainty in model outcomes.[45] Conditional probabilistic approaches have been used to explore whether scenario parameter uncertainty leads to divergent or (more commonly) convergent outcomes across scenarios.[43] Being computationally intensive, this method is less tractable for models with long run times, which constrains its application for many large-scale models. However, run times are also affected by the temporal and spatial resolution as well as the spatial extent of a model, and computational capacity is becoming increasingly less important.

Apart from these examples of scenario parameter uncertainty being quantified and communicated, there is little quantification of the uncertainties arising from different management and policy actions to achieve stylized scenarios,[2] e.g., assumptions of vegetarianism,[31] maximizing long-term fishing catches,[46] and the rate of change in fishing technologies that have been identified as key drivers of increasingly effective fishing effort that impacts marine biodiversity.[47] Management practices are especially important when representing adaptation processes within models in which responses are consistent with time-varying, scenario-specific barriers and enablers, e.g., societal values and governance.[48] Overall, there are considerable gaps in current knowledge about scenario parameter uncertainty.

Model uncertainty

Structural uncertainty

Models simplify the representation of the real world in different ways and so produce different responses to the same scenario assumptions. These responses depend on how a model is structured and parameterized and on the timescale, all of which can lead to structural model uncertainty. Hence, modeling is the art of making choices in a given context, and structural uncertainties reveal the variety of these choices.[49,50] The more knowledge we try to formalize within models through process-based understanding, the more uncertainty we may potentially cause or reveal. One could argue that simple, parsimonious models are better than complex models for robust forecasting,[51,52] but there is no universal evidence of a relationship between model complexity and model robustness. Parsimonious models that are based on observed trends may lead to low uncertainty within the range of conditions for which they were calibrated, but can lead to high uncertainty when applied over longer timescales or in scenarios with large deviations from current trends.[53,54] However, focusing on parsimony misses the point about why we build models. We model to experiment with elements of the natural world to explore, explain, and understand how they work.[51]

Many models of climate, land use, and biodiversity are increasing in complexity by the addition of components, processes, and model coupling.[55–57] More complex models may, arguably, be better at representing system dynamics over longer time scales or under changing conditions than simpler models.[58] For example, oversimplifying biodiversity representation in vegetation models has long been an impediment to detailed understanding and robust projections of ecosystem dynamics and distribution.[59,60] This has motivated a finer representation of species or traits diversity,[61–64] which allows better exploration of the role of the interactions between diversity and ecosystem functioning in shaping the future of natural systems.[65,66] However, this does not necessarily lead to less uncertainty, since the representation of feedbacks and path dependency may lead to dramatic changes in system behavior, potentially increasing the range of possible responses and associated uncertainty. Furthermore, increasing model complexity may also lead to problems with the traceability of the origins of uncertainty and inconsistencies between different model components.[67] These problems may be further compounded within models that include stochastic process representations, leading to internal variability and multiple model outcomes. However, stochastic approaches based, for example, on Monte Carlo methods can be useful in representing uncertainty in model structure.[68]

Models can support improved understanding of how resource management can adapt to environmental change and thereby inform decision-making and policy processes. However, a better representation of adaptation processes is required in models in general. For example, substantial differences have been found between the extensive, available empirical knowledge about societal adaptation processes and their representation in models of land and water sectors.[69] Only a minority of models take account of the management choices that underpin adaptation measures or the constraints (financial, institutional, social, etc.) that may limit the uptake and effectiveness of adaptation;[70] factors that are likely to be influenced (positively or negatively) by the scenario setting. The pervasiveness of simplistic, over-optimistic approaches to simulate the role of adaptation in reducing impacts and vulnerabilities or in exploiting the benefits associated with climate and socio-economic changes means that studies may produce findings that cannot meaningfully inform decision-making about appropriate adaptation strategies.

Incremental model improvement aims to increase a model's ability to predict plausible responses to uncertain, environmental change conditions. The drawback of incremental improvements is that they can cause "lock-in" of an existing model structure or ways of doing things.[71] Moreover, even incremental changes in model structure require substantial investment in time and effort. The exploration of alternative structural specifications in models is often done for local- to regional-scale studies.[72–74] At the global level, the investment required to build new models may be substantially larger than maintaining existing models. Global-scale models often need long-term institutional funding, thus limiting the number of research groups that have the capacity for such effort. Hence, the diversity of model structures and modeling paradigms is low in global-scale modeling compared with regional-scale models.[75] For example, many global-scale economic models still use optimization approaches based on the assumptions of neoclassical economics that are known to be limited.[76]

Better understanding of structural uncertainty is often achieved by trying to learn from model inter-comparison exercises[7,77] (see Box 1) for the comparison of model results with observed data.[78,79] Model inter-comparisons and the closely related ensemble modeling approach have proven highly beneficial for improving the credibility of climate change projections, such as through the Coupled Model Inter-comparison Project (CMIP).[80] Similar multi-model efforts, in which different models that address a similar question are run using a standardized simulation protocol and the same input data, are only starting for impact models projecting future terrestrial[2,75] and marine biodiversity (Fish-MIP).[33,81]

The comparison of model outputs with observational data,[106] or benchmarking, can provide pointers toward the conditions under which a model performs better or worse, as well as revealing the sources of uncertainty. Diverse sets of observations are needed to assess both the magnitude and seasonal and interannual variability of modeled outputs.[82] Specialized experiments, such as free-air carbon enrichment studies, herbivore exclosures, or remotely sensed trait information[90–92] can also be used to test the realism of specific simulated processes. Taken together, these datasets can be used to test whether models correctly capture existing relationships between variables (or incorrectly assume existing relationships, which are not supported by observations). At least for vegetation models, studies have begun to systematically explore the use of scoring of model performance against a range of observations.[82] Two further common approaches to model improvement are: (1) the addition or re-specification of certain model components and (2) the simple calibration of model parameters to increase the model fit to data. Calibration may lead to either overfitting of the model or

Box 1. Model benchmarking, inter-comparison projects, and ensembles

Benchmarking is the repeated confrontation of models with a range of observations to establish a track record of model developments. Observational datasets in themselves are uncertain,[82,83] so benchmarking needs transparent information on which observations were used. Some global models already routinely undergo a systematic confrontation against data when new processes are added (e.g., for the terrestrial carbon cycle).[84–89] Recent approaches allow scoring of model performance against a wide range of observations for global vegetation models.[82] Observational data for benchmarking include multiple-site and remote-sensing products of, e.g., fraction of absorbed photosynthetically active radiation, gross primary productivity, net primary productivity, burnt area, river discharge, or atmospheric CO_2 concentration. Specialized experiments or datasets, such as free-air carbon enrichment studies, herbivore exclosures, or remotely sensed trait information[90–92] can also be used to test the realism of specific simulated processes. Diverse data are needed to assess both magnitude and seasonal and interannual variability of modeled processes.[82] These datasets can be used to test whether models correctly capture existing relationships between variables (or incorrectly assume existing relationships, which are not supported by observations). Physics, climate, and biogeochemistry observations are generally more numerous, systematically measured, and available on different spatiotemporal scales, whereas biodiversity data are more disparate and contain many gaps (e.g., the GOOS marine initiative),[93] so benchmarking is much more challenging for biodiversity models.

In models of climate, oceans, and ecosystem dynamics, stochastic sensitivity analyses (sometimes called "perturbed physics experiments") are applied (see also section parameter uncertainty) where model-internal parameter values are sampled across a parameter-space to explicitly and transparently test parameter-value uncertainty.[94] These analyses are computationally expensive and, so, have not been sufficiently exploited with coupled and integrated models. But, a number of studies have demonstrated their application both in offline models (e.g., related to vegetation or land-use change modeling) and in coupled models (e.g., related to carbon cycle-climate feedbacks).[42,44,95–98] Results help to identify those parameters to which a model is most sensitive, but can also inform sensitivity analysis of other models for those values. The outcomes aid the interpretation of, e.g., model ensembles as the magnitude of uncertainty seen in a single model's output from stochastic parameter sensitivity analysis can be compared with the spread in output within a model ensemble.

The currently most widely used approaches to quantify model uncertainty in climate change, land-use change, exploitation, and ecosystem modeling are inter-comparisons and model ensembles.[7,99–102] Ensemble modeling has proven highly beneficial for improving the credibility of climate change projections with international model inter-comparison efforts such as the Coupled Model Inter-comparison Project (CMIP).[80] It is only starting for impact models projecting future terrestrial[2,75] and marine biodiversity (Fish-MIP).[9,103] In model inter-comparisons, different models that address a similar question are run using a standardized simulation protocol and the same input data. Output comparison helps to identify whether models agree or disagree in the simulated time series or spatial patterns. In some cases, an ensemble mean is used based on the notion that the average across a range of models would "average-out" some of the structural and parameter-related uncertainties and yield more robust results.[15,94,104] However, the comparison between individual models and the "ensemble mean" might unintentionally also lead to the model being "re-tuned" to fit better to the average model response. Furthermore, "families" of similar models (or with similar development heritage) tend to bias the mean, as they are each given the same weight as a genuinely different model. So far, most ensemble studies do not identify and exclude (or give different weight to) models that fail to fulfill certain quality-assurance criteria (based on scores in a benchmarking exercise). This has started, however, to be the case for the terrestrial models used in the annual global carbon budget calculation.[105] In view of the often still untested model structural and parameter uncertainties, deriving probabilistic estimates of uncertainty from model ensembles must be viewed critically.[94]

to issues relating to equifinality. In overfitting, a calibrated model may represent a specific place and time very well, but it sacrifices generality when applied to other places and times. The comparison between individual models and an "ensemble mean" might unintentionally also lead to the model being "re-tuned" to fit better to the average model response.

Equifinality occurs when different functional or process representations in a model lead to the same outcome.[107–109] This reduces the range of the modeled outputs, but at the same time may conceal structural uncertainty, since it can be difficult to track which mechanisms within a model lead to the equifinal outcomes. The effect of equifinality can be evaluated by comparing the overall model outcomes against independent datasets,[58] but also by comparing different process representations within the model itself. This is important when assumptions are made, for example, in how to model the management choices that underpin land-use change.[110] While different approaches to representing management choices may, in the short term, lead to similar land-use outcomes, they may wrongly represent longer-term adaptation and behavior under resource constraints. In this case, empirical data on management choices may be more useful in validating the model process than validating the short-term model outcomes.

In a review of land-use models, little over half were validated independently, and many conflated calibration with validation.[70,111] Although this can be explained to some extent by the limited availability of consistent empirical datasets for different time periods, it still increases the risk of overfitting in many model applications. In other words, a model both trained and validated on historical data may not accurately project the full range of outcomes in a non-stationary future. However, calibration to improve model fit can, in part, compensate for the subjective decisions made by modelers concerning the selection of observed input datasets (e.g., which meteorological, economic, or demographic variables), alternative process algorithms (e.g., reference evapotranspiration), and initial conditions (e.g., land-use classes and their distribution).[112,113] Nevertheless, the consequences of these choices may still be unclear when the model is perturbed beyond the historical conditions represented in the calibration data, leading to potentially large uncertainty in the magnitude and direction of impacts.[113]

Input data uncertainty

It is difficult to decouple model structural uncertainty from model input data uncertainty, since models with a different structure commonly use different input data.[7,104] Models of socio-ecological systems are data demanding for parameterization, calibration, and initialization of simulations, including large demands for baseline data. Uncertainties in the use of data can emerge from measurement errors, data scarcity, or a mismatch between the resolution and scope of the available data, and the needs of the model. These uncertainties are amplified when models include additional processes, represent processes at finer spatial scales, or expand the spatial and temporal scope of simulations. For example, data availability has been assessed for several mechanisms known to play a key role in mediating species responses to climate change, such as physiological processes, evolutionary potential, and species interactions.[114] Even for the best-studied species, data were at best incomplete if not entirely absent. In recent years, the scientific community has gone to great lengths to increase access to biodiversity data through the development of networks of high-quality monitoring systems (observation systems, instrumented sites, and remote-sensing sensors),[115–118] data repositories (e.g., GBIF.org; obis.org), or citizen science programmes.[119–121]

For correlative species distribution models,[122,123] the lack of accuracy and comprehensiveness of the species data and of the relevance and completeness of the predictors can critically impact the relevance of the fitted niche models and hence of the resulting outcomes.[124,125] Data deficiencies and biases in this specific approach include samples of species' occurrences that are too small or do not include absences, or have missing covariates; the latter being known to introduce significant spatial correlation in the errors of the analysis.[126–129]

Trait-based approaches have been developed to leverage limited data and allow model prediction for a broad range of species, including poorly studied ones. Traits are individual features that inform individual performance.[130] Both correlative and process-based models have used trait parameters to simulate higher-level processes. This includes population growth rate or range shifts in plant,[64,131–133] fish,[134–136] or reptile and amphibian communities.[137] Trait data availability is increasing rapidly (e.g., open digital repository;[138,139] www.fishbase.org), but it remains highly variable across taxonomic groups and geographic areas. It is also strongly correlated with the ease in measuring traits: so-called "soft" structural traits have been more often measured than "hard" physiological traits, although the latter often provide key information on species responses to non-present analog conditions, such as tolerance to drought or higher temperatures.[140–142] In addition, functional ecologists often report species mean trait values, resulting in a lack of assessment of intraspecific trait variability[142] despite increasing evidence for its role in species adaptation and coexistence.[143–146] These are both crucial in establishing biodiversity projections.[147]

Uncertainties related to initial conditions are less well studied in socio-ecological models,[148] although they have been identified as important in some studies. For example, variability in the data used to represent initial land-use conditions between different models of land-use change contributed a substantial part to the variation across future land-use projections[7] with distinct spatial differences in the level of uncertainty.[104] Differences in initial data can arise from different definitions of the same land cover type and different data acquisition approaches.[7,104] Similarly, errors in the initialization of forest structure in large-scale simulations of vegetation models can result from limited sampling and coarse resolution (for example, of large-scale, remote-sensing products), and have been found to propagate in subsequent model prediction uncertainty.[73,149,150]

Several methods are available to address input data uncertainties. Hierarchical modeling techniques and other statistical methods can address different sources of uncertainty explicitly in modeling frameworks.[146,151,152] Sensitivity and uncertainty analyses[43,153,154] can help identify and prioritize the need to reduce parameter uncertainty given limited time and resources and hence guide the empirical effort of data collection through iterative cycles of data-model fusion.[16,155,156] In stochastic sensitivity analyses (sometimes called "perturbed physics experiments"; see Box 1) model-internal parameter values are sampled across parameter-space to explicitly and transparently test parameter-value uncertainty.[94] These analyses are computationally expensive and, so, have not been sufficiently exploited with coupled and integrated models. But, a number of studies have demonstrated their application both in offline models (e.g., related to vegetation or land-use change modeling) and in coupled models (e.g., related to carbon cycle-climate feedbacks).[42,44,95–98] Results help to identify and rank those parameters to which a model output is most sensitive, but can also inform sensitivity analysis of other models for those values. The outcomes aid the interpretation of, e.g., model ensembles as the magnitude of uncertainty seen in a single model's output from stochastic parameter sensitivity analysis can be compared with the spread in output within a model ensemble.

Data assimilation techniques can bridge the gap between data availability and model requirements. In particular, inverse modeling, such as approximate Bayesian computation use a wide range of data to refine values of input parameters.[157–160] With these methods, parameter distributions provided by the available data (prior parameter estimate) are iteratively adjusted (posterior parameter estimate) by comparing simulation outputs with observed data at different scales, e.g., element fluxes derived from eddy-flux measurements,[161] tree size distribution derived from inventory data,[162] or remote-sensing products.[163]

A promising avenue in terms of data assimilation is the spectrometry imagery of functional diversity,[90,164] which, at least for terrestrial ecosystems, can help to bridge the gap between biodiversity data available from field surveys and the amount of data required to better control for uncertainty in continental- and global-scale models. This raises new technical challenges in terms of data standardization (corrections and inter-calibration of remote-sensing images) and methods for data extraction.[165] It also raises the issue that the input data themselves often derive from modeled products. For example, in modeling the terrestrial C-cycle, the same level of uncertainty is possible for several DGVMs forced by the same climate scenario (based on a single emissions scenario and climate model), as for a single DGVM forced by inputs from several climate scenarios (with different emissions and climate models).[166]

Error propagation uncertainty

Uncertainties from error propagation arise in coupled model systems when the inputs to one model (e.g., a model of climate impacts on ecosystems) derive from the outputs of another model (e.g., a climate model). In some cases, several models are coupled together leading to serious error propagation especially at the end of the chain of coupled models.[167,168] Error propagation becomes even more important when there are dynamic feedbacks between models.

Coupled models are common in integrated assessment, which seeks to explore the interactions between, as well as within, different socio-ecological systems.[56] Integrated assessment models (IAMs) focus, for example, on the connections between the economy, the energy system, and land cover change[169] at global-scale levels. However, regional IAMs have also demonstrated the importance of adopting a cross-sectoral approach for impact assessments.[37] Indeed, the impacts of climate change as reported by the IPCC may be over- or underestimated because they fail to account for cross-sectoral interactions.[37] A source of uncertainty in coupled models is when simplified, meta-models replace complex models to facilitate data flows across systems.[37,153] However, these uncertainties may be acceptable since the indirect effects of one sector on another sector are often more important than the changes within a single sector itself.[37] Similar issues arise for models that do not consider cross-scale impacts, since one scale level is highly dependent on the boundary conditions defined by a higher-scale level.[76]

Different methods can evaluate the uncertainties arising from error propagation, with qualitative methods being of particular utility. Dunford et al.[168] combined formal numerical approaches, modeler interviews, and network analysis to provide a holistic uncertainty assessment of a regional integrated assessment model that considered both quantifiable and unquantifiable uncertainty. Maps of modeler confidence (the counterpart of uncertainty) were created from fuzzy-set methods and network analysis to show that validation statistics are not the only factor driving modeler confidence. Several other factors, such as the quality and availability of validation data, the meta-modeling process, trust between modelers, derivation methods, and pragmatic factors, such as time, resources, skills, and experience were also found to be important.[168]

For most simple models (e.g., linear Gaussian models), the variance of the prediction associated with error propagation can be computed analytically, paying attention to the dependence between variables and the associated covariance.[170] In the majority of cases, modeling involves complex models that are non-linear and non-Gaussian for which variance computation is analytically intractable. In such cases, error propagation can be evaluated through simulation using, for example, Monte Carlo methods.[171] A Monte Carlo-based approach to evaluate the propagation of uncertainties in a regional integrated assessment model, showed that, rather than the uncertainties "exploding" in importance, there was convergence across a range of contrasting scenarios.[43] This implies that if fully understood, uncertainties arising from error propagation can be managed successfully. However, the assessment of error propagation through simulation is computationally demanding and, in general, only applicable to models with rapid run times.

Model output-input chains and feedbacks can become complex and lead to unacceptable levels of uncertainty for decision-making.[168] Where possible, major sources of uncertainties (data, model, parameters) should be identified a priori to allow propagating errors with a minimum number of simulations. Comprehensive sensitivity analysis is also useful in identifying emergent uncertainties.[153] Structured sensitivity analysis (also referred to as scenario-neutral approaches and impact-response surfaces) is valuable in evaluating whether the emergent behavior in coupled models as a response to simple perturbations is consistent with understanding or influenced by error propagation, although sensitivity analysis as a method has been criticized.[172] Hierarchical Bayesian models can be useful tools to incorporate and propagate errors from multiple sources (data, parameters, models), through the computation of the predictive posterior distribution.[173]

UNCERTAINTIES IN DECISION-MAKING AND DECISION METHODS

Intrinsic uncertainties in decision-making

Uncertainty pertaining to environmental processes and ecological theory is interesting from an academic perspective, but it becomes a practical issue when it impinges on the ability of managers, planners, and policy makers to make relevant science-based decisions to achieve societal objectives.

Despite multiple uncertainties, decisions are still made about natural resource management. However, the decision-making process is itself messy and difficult to predict, depending as it does on the context, on the individuals involved (with their conscious and unconscious biases), on the breadth of values attributed to nature (including non-quantifiable ones), on the efficient exchange of knowledge between science and policy, and on time lags in policy implementation.[174] Decision-making is often disorganized and politicized, and has to deal with many trade-offs, as well as co-benefits, making it difficult to generalize about how uncertainty in scenarios and models affects decision-making processes. There is a significant body of work in decision theory and operations research on dealing with epistemic uncertainty in decision-making. However, further understanding is still needed on the relationship between science and the social and political processes of decision-making, and this is an important area of future research in environmental management.

What can be stated is that different degrees of uncertainties and levels of controllability may be more effectively managed by different strategies and approaches.[3] Controllability here refers to the degree of control that a decision-maker has over the system being managed. Controllability tends to be higher when decision horizons are shorter, when the decision-maker has direct and sole jurisdiction over the places and/or resources being managed, or when stakeholders do not vary widely in their aspirations for the outcomes of management. Controllability covaries with uncertainties over temporal and spatial scales. It tends to be higher at local and national scales relative to regional and global scales.[175] When the system is highly controllable, and uncertainties about the future are low, it may be most effective to implement optimal control tactics. Optimal control tactics generally involve "predict-then-act," such as determining catch or fishing quotas.[176] In situations where controllability is low and uncertainty is high, robustness analysis[177] in support of scenario planning[178] may be favored.[179]

In this section, we further discuss how uncertainties in scenarios and models can contribute to decision-making uncertainty, as well as the tools that are available to address these uncertainties and their limitations.

How uncertainties are communicated to decision-makers

How uncertainties are accounted for in decision-making is strongly dependent on how these uncertainties are communicated to decision-makers. In international science-policy processes, such as IPCC or IPBES, formalized uncertainty language is used to communicate levels of confidence in the assessment of scientific evidence,[180] including results from scenarios and models. This approach is generally qualitative, although attempts have also been made to use quantitative probabilistic statements. Whether this approach is effective in communicating uncertainty to policy communities is debatable,[181] although some benefit to decision-makers is likely since government-approved assessment reports continue to use uncertainty language.

How uncertainties are accounted for in decision-making is also strongly dependent on how these uncertainties manifest into the different indicators that are provided to decision-makers, e.g., Living Planet Index,[182] species richness,[183] extinction risk,[184] and monetary value of ecosystem services.[185] Communicating alternative scenario outcomes thus requires appropriate indicators that are understandable and meaningful to decision-makers, and above all responsive to different drivers in an expected way, i.e., with low uncertainty. Within the same scenario or model, the way the output variables are transformed, integrated, and combined into indicators does not result in the same level of uncertainty,[186] or in the same strength of the signal-to-noise ratio.[185] The granularity of an indicator can be key (from population, to multispecies, to whole community level for example), as well as the choice of the spatial and temporal scales at which it is integrated. The portfolio statistical concept developed in economics and used by analogy in ecology, explains why dynamics may be extremely volatile at small scales (and high biodiversity granularity, e.g., population biomass), but less variable at more aggregated scales (and low biodiversity granularity, e.g., community biomass).[187] International initiatives, such as the Group on Earth Observations Biodiversity Observation Network (https://geobon.org), the Global Ocean Observing System (www.goosocean.org), and the Biodiversity Indicators Partnership (www.bipindicators.net), have proposed a number of indicators and essential biodiversity variables to characterize changes in biodiversity status under global change. However, the selection of indicators has been done mostly under the criteria of measurability and accessibility at the global scale,[116,118] but the performance of indicators in capturing changes and associated uncertainty have rarely been tested in a systematic way.[188,189]

It is not possible to say whether communicating to decision-makers the uncertainties in scenarios and models of socio-ecological systems actually changes decision-making in practice or not. There is no objective measure of the "success" of communicating uncertainties, nor is there a counterfactual to explain whether alternative decisions would have been made in the absence of knowledge about uncertainties.

How decision-making tools address uncertainties

A great number and variety of tools exist to support decision-makers in dealing with various kinds of uncertainty when making decisions.[6] A key role of decision support tools is to provide a framework that allows decision-makers and stakeholders to separate deliberations about what represents a desired outcome (competing objectives and preferences that arise from differing values) from deliberations about the facts of the matter; the probability that a particular course of action will result in a particular outcome. Therefore, it can be useful to think about different decision support tools in terms of how they deal with competing values and uncertainty (see Figure 2).

Decision support tools vary in terms of how they deal with spatial scale and extent, cultural and administrative complexity, multiple stakeholders, and competing values and uncertainty.[6] In Figure 2, we outline a small sample of the decision support approaches that deal with uncertainty to varying degrees with the aim of highlighting the breadth of opportunities for addressing competing values and models using existing decision support approaches, and these approaches are summarized in Table S1.

Despite the widespread development of decision support tools, the capacity of these tools to support objective decision-making may often be limited, especially where high levels of complexity and uncertainty make interpretability difficult. For example, when uncertain trade-offs between different ecosystem services are at stake, tools designed to support decisions are usually required to impose artificial boundaries or quantifications, and to limit and render comparable the broad, diverse range of services in question.[190–193] This implicitly involves the same value-based judgment under uncertainty that a decision-maker would be faced with in the absence of such a tool, but often obscures its subjective nature. More systematic biases also exist. Knowledge about socio-ecological systems is growing so rapidly and on so many fronts that it is very difficult to capture accurately. Social science knowledge in particular is consistently neglected, perhaps because most tool developers are natural scientists.[194,195] This also contributes to the neglect of cultural services, and their uncertainties, in ecosystem services assessments.[196] Even tools that sacrifice coverage are likely to prove to be too complex and uncertain to be used and understood by stakeholders as originally intended.[190]

Decision support tools therefore run the risk of obscuring uncertainty and subjectivity rather than helping to overcome it. This can be revealed, and to some extent overcome, where tools are used in participatory settings that allow for interrogation of assumptions, representation, and outcomes by a range of stakeholders.[197] Comprehensive uncertainty evaluation can

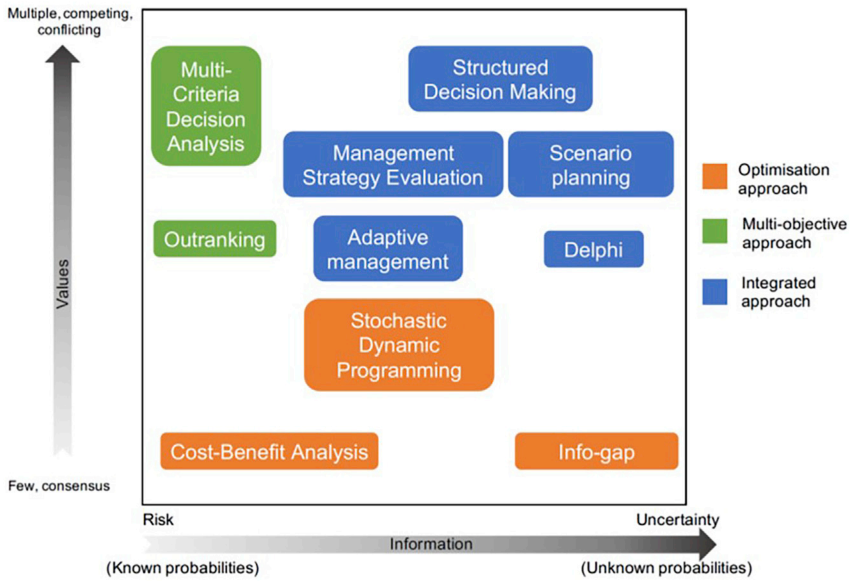

Figure 2. A sample of decision tools to support decision-making in the presence of competing values and uncertainty
See Table S1 for tool summaries and key references. Optimization approaches (orange) are a broad family of approaches that utilize either simple (cost benefit) or more sophisticated (info-gap) mathematical formulations that maximize an objective function. Multi-objective approaches (green) focus more on characterizing the competing values and preferences of decision stakeholders through more deliberative, or sometimes hybrid deliberative/quantitative processes. Integrated approaches (blue) tend to bring a suite of deliberative and quantitative tools together into a framework that seeks good decisions (e.g., Adaptive Management and Structured Decision-Making).

play an important role in this process,[198] but is not itself sufficient. Rather, improved and more comprehensive methods of accounting for subjectivity and uncertainty within nominally objective decision processes remain a priority.[199]

DISCUSSION: WAYS FORWARD

It is important to recognize the many sources of uncertainties that exist in scenarios and models of socio-ecological systems. It is also important to avoid these uncertainties becoming a disincentive for action when facing environmental challenges, within either the science or decision-making domains. Importantly, decision-makers should not use uncertainty as an excuse for inaction. There is no panacea for dealing with uncertainty, but a portfolio of approaches may provide an opportunity to better understand and cope with uncertainty. This portfolio might include a range of methods from Model Inter-comparison Projects (MIPs), validation against independent data, error propagation analysis, to learning from uncertainty to guide model improvement. Table 2 provides a summary of the approaches to addressing uncertainty that are discussed throughout this article. Figure 3 also provides a visual representation of these approaches with referencing to Table 2. Together, these provide a checklist of the types of actions that can be implemented when dealing with uncertainties of scenarios and models of socio-ecological systems within the context of supporting decision-making.

A number of ways of dealing with uncertainty are still not routinely applied in scenario modeling and this is becoming increasingly unacceptable. For instance, statistical parameter uncertainty analysis may not be possible for all parameters for all models, but it can be done at least for a subset of model parameters. Likewise, the confrontation of models with data is inadequately done. In many cases, there may be insufficient data to do this properly, but using this as an excuse to do nothing at all is simply wrong. In situations where data are lacking, one should start with qualitative "common sense" tests, such as by Turner et al.,[200] who identified future projected rates of change in bioenergy adoption to be three times faster than the historical precedent for the most rapidly changing land use.

Likewise, creating better scenarios of uncertain futures would benefit from consideration of a wider range of socio-economic and natural system drivers going beyond a focus on climate change alone.[2] This includes, for instance, drivers of biodiversity loss, such as biomass extraction, invasive alien species, and pollution.[2] Many scenarios are also weak at relating indirect drivers (i.e., the underlying socio-economic-political causes of change) to direct drivers. We need to move beyond the representation of stylized scenarios of, for example, consumption patterns, to scenarios and models that account for the role of human behavioral processes in affecting ecological change. This includes better representation of how policy and conservation initiatives affect people with the knock-on effects this has for ecosystems.[201] This is critical in better evaluating the considerable role of humans in causing ecological degradation, and in informing the decision processes that can do something about it through restoration and effective ecosystem management.[202]

Within this review, we have focused on models and scenarios of socio-ecological systems. However, it is clear from the literature that there is a bias toward the "ecological" aspects rather than the "social" aspects of such systems, such that many modeling approaches do not adequately capture the full range of interacting human and natural processes. We view this as a major research gap in current modeling and scenario exercises, and suggest that further development in this field would benefit from a greater focus on the social phenomena that are critical in understanding the functioning of nature on a human-dominated planet.

Uncertainty is often seen as the problem, while instead it could be interpreted as a "space" to manage socio-ecological systems in more desirable directions. Uncertainty also helps to target future effort in model development and to identify areas that lack understanding and, so, are priorities for future research. However, structural uncertainty needs to go beyond the improvement of model components and details, by re-evaluating the fundamental principles and assumptions of a model structure. Furthermore, part of the total uncertainty in the future of

Table 2. Potential solutions and recommendations to address uncertainty in models and scenarios of socio-ecological systems for different sources of uncertainty

	For these sources of uncertainty								
	Scenario uncertainty			Model uncertainty			Decision-making uncertainty		
Potential solutions and recommendations	Storyline	Linguistic	Parameter	Structural	Input	Error propagation	Tools	Communication	Interpretation
1. Stakeholder mapping exercises to address uncertainty in participatory processes	✓								
2. Explicitly state and document the assumptions that underpin a scenario narrative, and communicate these assumptions when reporting a scenario study	✓	✓							
3. Building ontologies		✓							
4. Defining credible scenario parameter ranges or using conditional probabilistic methods			✓						
5. Considering a wider range of socio-economic and natural system drivers that go beyond a focus on single drivers alone, e.g., climate change			✓						
6. Model inter-comparison exercises and model ensembles			✓	✓					
7. Developing coupled socio-ecological systems models that identify and represent important feedbacks to support the inclusion of feedbacks in scenarios			✓	✓					
8. Model benchmarking (see Box 1)				✓					
9. Validation against independent data, including the confrontation of models with empirical data				✓					
10. Going beyond the improvement of model components and details, by re-evaluating the fundamental principles and assumptions of a model structure				✓					
11. Developing scenarios and models that better account for the role of human behavioral processes in affecting ecological change				✓					
12. Learning from uncertainty to guide model improvement				✓					
13. Qualitative "common sense" tests, where independent validation data are lacking				✓	✓				

(*Continued on next page*)

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Table 2. *Continued*

	For these sources of uncertainty								
	Scenario uncertainty			Model uncertainty			Decision-making uncertainty		
Potential solutions and recommendations	Storyline	Linguistic	Parameter	Structural	Input	Error propagation	Tools	Communication	Interpretation
14. Hierarchical statistical modeling techniques and other methods, such as sensitivity and uncertainty analyses				✓	✓				
15. Increasing data access, e.g., developing high-quality monitoring systems (observations, instrumented sites, and remote-sensing sensors), data repositories, or citizen science					✓				
16. Data assimilation techniques, such as inverse modeling, e.g., approximate Bayesian computation					✓				
17. Error propagation analysis through, for example, qualitative methods, formal numerical approaches, modeler interviews, and network analysis						✓			
18. Simulation using, for example, Monte Carlo methods						✓			
19. Application of decision support tools to policy questions							✓	✓	
20. International initiatives to standardize indicators and make them available								✓	
21. Systematic testing of the performance of indicators in capturing socio-ecological changes and associated uncertainty								✓	
22. Defining appropriate indicators that are clear, concise, and responsive to different drivers								✓	
23. Improved and more comprehensive methods of accounting for subjectivity and uncertainty within nominally objective decision processes									✓
24. Co-creation and decision support in a participatory setting that allows for interrogation of assumptions, representation, and outcomes by a range of stakeholders	✓								✓

See Table 1 and the visual presentation in Figure 3. This list does not preclude other relationships between solutions and uncertainty sources that may be feasible.

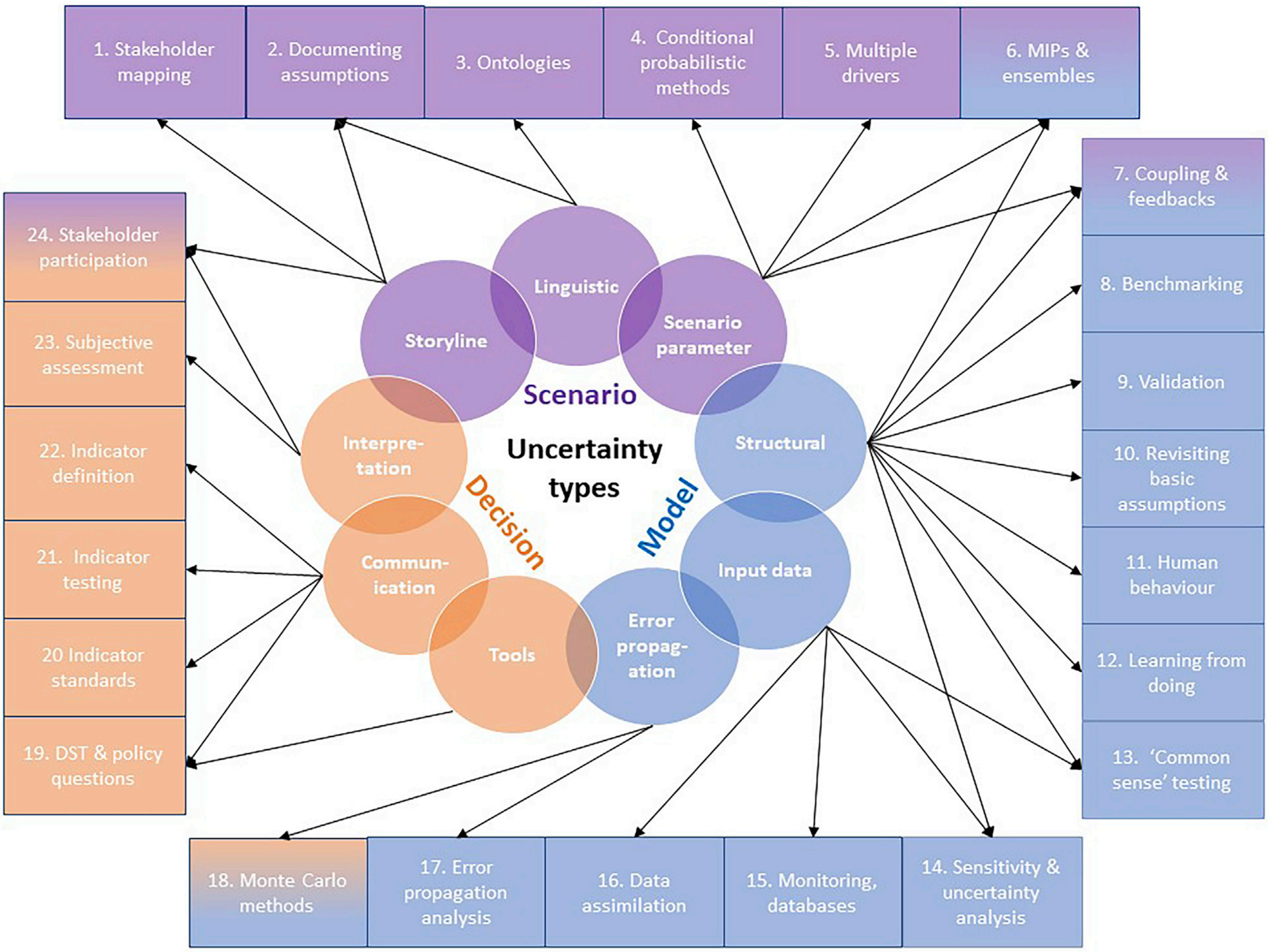

Figure 3. Visual summary of the types of uncertainties in scenarios and models of socio-ecological systems and ways of addressing them
The uncertainties are categorized as scenario, model, and decision uncertainties (see Table 1). More details about the numbered methods for addressing uncertainties are provided in Table S1. The color coding refers to the sources of uncertainty (see Table 1), with the gradient-shaded boxes indicating methods that apply to more than one uncertainty source.

socio-ecological systems actually derives from current and future decisions and, thus, from a decision-maker or citizen point of view, represents less of an "uncertainty" than our "societal leeway" or choices. Disentangling and documenting the different sources of uncertainties in socio-ecological systems is critical in allowing the design and initiation of informed and efficient actions. Many things about the future will always be uncertain, but we may wish to avoid the foolish and the fanatical by adopting the wisdom of doubt. Data and knowledge about socio-ecological systems are increasing rapidly, and knowledge improvement is often concomitant with awareness raising about system complexity. This leads to the paradox that, as technical knowledge increases, what we ignore is increasingly more important than what we know.

Uncertainty in science should not imply uncertainty in making decisions that respond to environmental problems.[203] Ironically, scientists see the quantification of uncertainty as underpinning scientific rigor, whereas others see it as a sign of weakness in the underlying science.[204] Too often, such a fallacy has become a flawed means of discouraging the endorsement of policies against environmental problems, such as climate change or biodiversity. Knowledge of uncertainty should inspire action rather than indifference and guide decision-making, rather than prevent it.[203]

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.oneear.2021.06.003.

ACKNOWLEDGMENTS

This work is part of the USBIO project funded by the LabEx CeMEB (ANR-10-LABX-04-01). M.D.A.R., A.A., and C.B. would like to acknowledge the funding of the Helmholtz Association. Y.-J.S. acknowledges funding support from the Biodiversa and Belmont Forum project SOMBEE (BiodivScen ERA-Net CO-FUND program, ANR contract no. ANR-18-EBI4-0003-01), the European Union's Horizon 2020 research and innovation program under grant agreements no. 869300 (FutureMARES) and no. 817578 (TRIATLAS), and the Pew Fellows Program in Marine Conservation at The Pew Charitable Trusts. R.P.

was partly funded by the FACCE Era-Gas project 3DForMod (ANR contract no. ANR-17-EGAS-0002-01). O.G. was partly funded by CNRS "Mission pour l'interdisciplinarité" through its "Osez l'interdisciplinarité" call and the French National Research Agency (grant ANR-16-CE02-0007). W.W.L.C. acknowledges funding support from NSERC Discovery Grant (RGPIN-2018-03864). B.A.W acknowledges funding from the Australian Research Council under ARC DP170104795. Natasha Cadenhead assisted in production of Figure 2.

AUTHOR CONTRIBUTIONS

All authors contributed to the conceptualization, writing, and editing of the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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