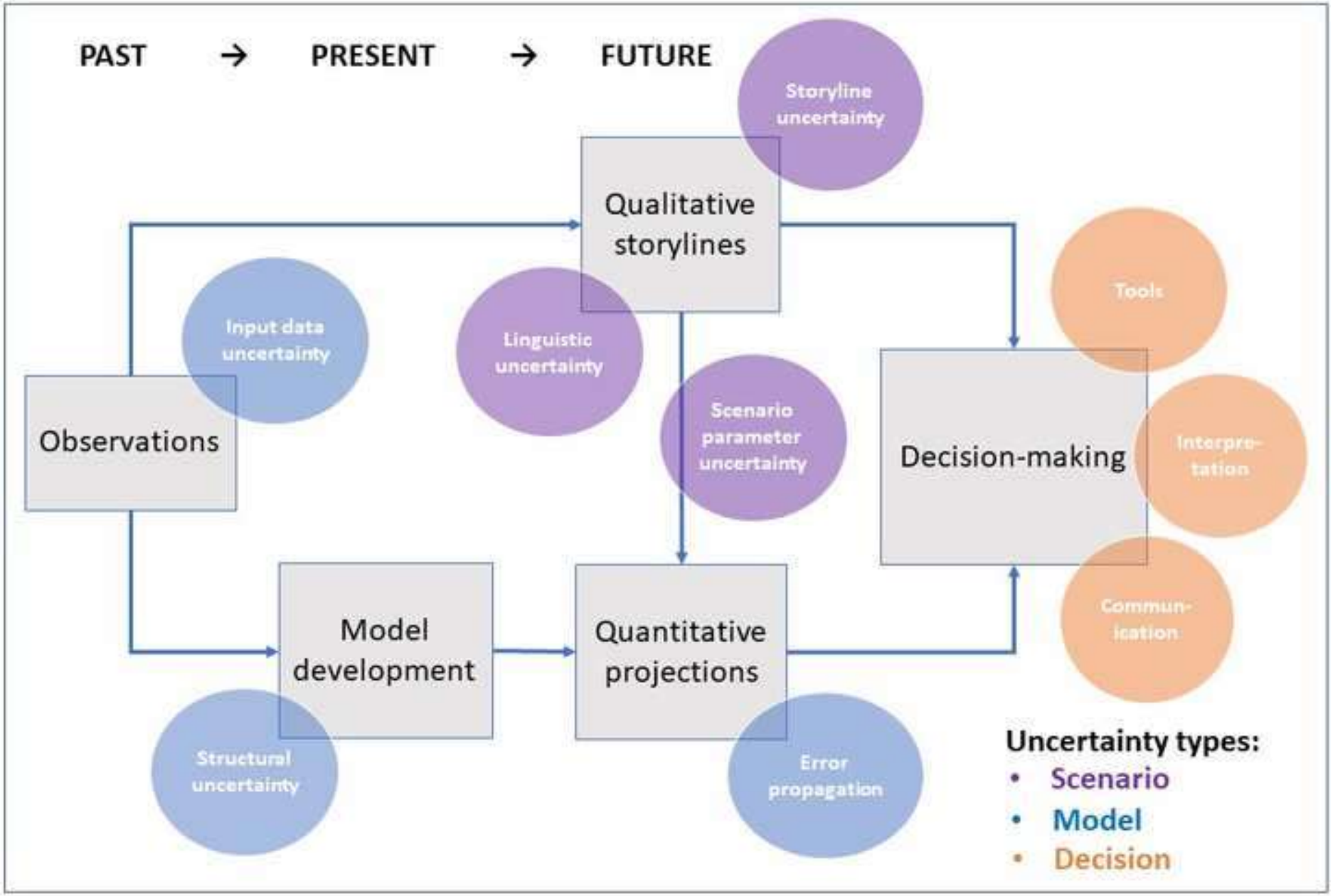
Graphical Abstract



Combined Manuscript File

One Earth, Volume 4, Issue 7, July 2021, pp. 967-985
DOI:10.1016/j.oneear.2021.06.003

Uncertainties in scenarios and models of socio-ecological systems and the implications for decision-making

Mark D.A. Rounsevell[1,2], Almut Arneth[1], Calum Brown[1], William W.L. Cheung[3], Olivier Gimenez[4], Ian Holman[5], Paul Leadley[6], Criscely Luján[6,7], Stéphanie Mahevas[8], Isabelle Maréchaux[9], Raphaël Pélissier[9], Peter H. Verburg[10,11], Ghislain Vieilledent[9], Brendan A. Wintle[12], Yunne-Jai Shin [7,13]

[1]*Karlsruhe Institute of Technology, Institute of Meteorology and Climate Research / Atmospheric Environmental Research (IMK-IFU), Garmisch-Partenkirchen, and the Department of Geo-ecology (IFGG) Karlsruhe, Germany*

[2]*School of GeoSciences, University of Edinburgh, Drummond Street, Edinburgh, EH8 9XP, United Kingdom*

[3]*Changing Ocean Research Unit, Institute for the Oceans and Fisheries, the University of British Columbia, Vancouver, B.C., Canada, V6T 1Z4*

[4]*CEFE, CNRS, University Montpellier, University Paul Valéry Montpellier 3, EPHE, IRD, Montpellier, France*

[5]*Cranfield Water Science Institute, Cranfield University, Bedford MK43 0AL, United Kingdom*

[6]*Laboratoire d'Ecologie Systématique Evolution, Université Paris-Saclay, CNRS, AgroParisTech, Université Paris-Saclay, 91400, Orsay, France.*

[7]*Institut de Recherche pour le Développement, MARBEC (Univ Montpellier, IRD, Ifremer, CNRS), Montpellier, France*

[8]*EMH, Ifremer, Centre Atlantique - Rue de l'Ile d'Yeu - BP 21105 - 44311 Nantes Cedex 03, France.*

[9]*AMAP Lab, University of Montpellier, CIRAD, CNRS, INRAE, IRD, F-34000 Montpellier, France*

[10]*Institute for Environmental Studies, VU University Amsterdam, de Boelelaan 1087, 1081 HV Amsterdam, the Netherlands*

[11]*Swiss Federal Research Institute for Forest, Snow and Landscape Research (WSL), Birmensdorf, Switzerland*

[12]*School of Ecosystem and Forest Science, University of Melbourne, 3010, Australia*

[13]*University of Cape Town, Cape Town, South Africa*

Summary

We review sources of uncertainty in scenarios and models of socio-ecological systems and discuss these in light of consequences for decision-making. We track uncertainty across the whole chain of 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 also propose solutions for how to deal with these uncertainties. Failing to appreciate the full scope of uncertainty can lead to over confidence in the predictive power of scenarios and models, but several approaches are available to quantify the many sources of uncertainty. Hence, uncertainties should not preclude policy action, but rather be seen as a key contribution to robust decision-making. Thus, successful application of scenarios and models in global change research requires careful evaluation of uncertainty and a sustained dialog between scientists and end-users about the sources of uncertainty and their implications for decision-making.

Key words: Uncertainty, scenarios, socio-ecological models, decision-making

Published by Cell Press. This is the Author Accepted Manuscript issued with: Creative Commons Attribution Non-Commercial No Derivatives License (CC:BY:NC:ND 4.0).
The final published version (version of record) is available online at DOI:10.1016/j.oneear.2021.06.003. Please refer to any applicable publisher terms of use.

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, 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], including behavioural 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 modelling 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. Throughout this paper, we explore uncertainties through the lens of specific model examples and outline potential solutions to dealing with these uncertainties.

Identifying and quantifying future uncertainties may be key in achieving buy-in from stakeholders, to prompt evidence-based decision-making, and to shift mind-sets on the perception of the future threats to biodiversity, ecosystems and ecosystem services. To increase the influence of scenario and modelling analyses on policy and to trigger appropriate management responses, the Intergovernmental science-policy Platform on Biodiversity & 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 organisations. In doing so, we seek to address some of the key challenges raised by Elsawah et al. (2020)[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. The objective of this paper is not 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 (2016)[3] assessment of scenarios and models.

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 initialisation 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 (past), model development (present), the construction of qualitative storylines (future) and quantitative scenario projections (future) that together provide input to decision-making.

The objective of this paper is to 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. It 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.

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 world-views 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 world-views 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 initialise 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-modelling and indirect effects (such as cross-sectoral interactions).

Decision uncertainty	Communicating and translating the results of scenario and modelling studies into decision-making.	*Data interpretation for decision-making.* Selective use of data or information from different sources and their interpretation. *Analysing at relevant spatio-temporal scales.* The selection of spatio-temporal scales at which simulated data are analysed, 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.

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 theatre. 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].

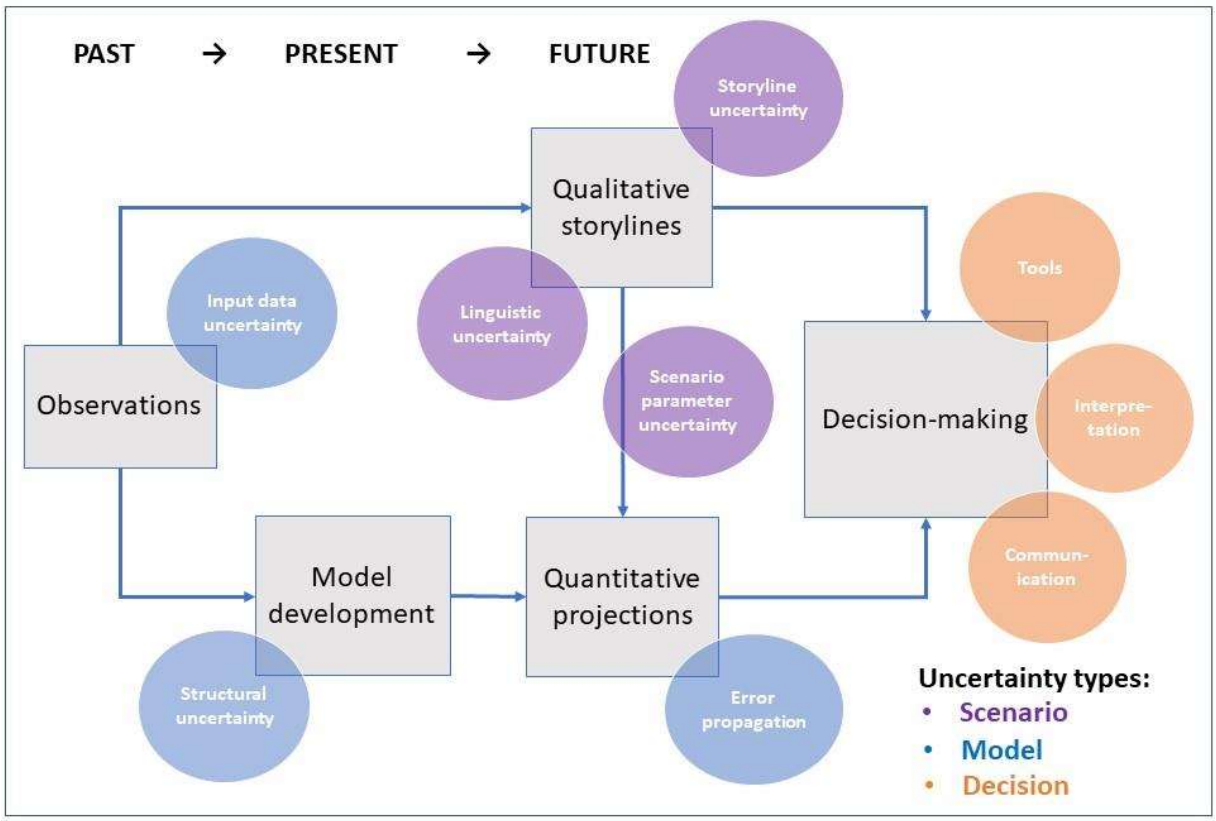


Figure 1. Sources of uncertainty in scenarios and models of socio-ecological systems within the context of decision-making. The circled sources of uncertainty are addressed in the main text: purple refers to scenario uncertainty, blue to model uncertainty and orange to decision uncertainty.

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 industrialisation[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 analogues 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 'stylised' 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 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 maximise 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 modelled 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 analogues. 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 'stylised' 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 parameterised and on the timescale, all of which can lead to structural model uncertainty. Hence, modelling 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 time scales 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 in order 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 behaviour, 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 global change impacts and adaptation to inform decision-making and policy processes. However, 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 which 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 adaptation decision-making.

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 maybe 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 modelling paradigms is low in global-scale modelling compared with regional scale models[75]. For example, many global scale economic models still use optimisation 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 Annex 1) or the comparison of model results with observed data[78,79]. Model inter-comparisons and the closely related ensemble modelling 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 standardised 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[82], or benchmarking, can provide pointers towards 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 modelled outputs[83]. Specialised experiments, such as free-air carbon

enrichment studies, herbivore exclosures or remotely-sensed trait information[84–86] 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[83]. 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 increased uncertainty due 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[87–89]. 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[90]. 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 behaviour 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[70,91]. 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. However, calibration to improve model fit can, in part, compensate for the

subjective decisions made by modellers 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)[92,93]. 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[93].

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[7,94]. 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[95]. 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)[96–99], data repositories (e.g. GBIF.org; obis.org) or, citizen science programmes[100–102].

For correlative species distribution models [103,104], 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[105,106]. 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[107–110].

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 [111]. 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[64,112–114], fish [115–117], or reptile and amphibian communities[118]. Trait data availability is increasing rapidly (e.g. open digital repository[119,120]; 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 analogue conditions, such as tolerance to drought or higher temperatures[121–123]. Additionally, functional ecologists often report species mean trait values, resulting in a lack of assessment of intraspecific trait variability [123] in spite of increasing evidence for its role in species adaptation and coexistence [124–127]. These are both crucial in establishing biodiversity projections[128].

Uncertainties related to initial conditions are less well studied in socio-ecological models [129], 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[94]. Differences in initial data can arise from different definitions of the same land cover type and different data acquisition approaches[7,94]. 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 [73,130,131].

Several methods are available to address input data uncertainties. Hierarchical modelling techniques and other statistical methods can address different sources of uncertainty explicitly in modelling frameworks [127,132,133]. Sensitivity and uncertainty analyses [43,134,135] 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[16,136,137]. In stochastic sensitivity analyses (sometimes called "perturbed physics experiments"; see Annex 1) model-internal parameter values are sampled across parameter-space to explicitly and transparently test parameter-value uncertainty[138]. 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 modelling) and in coupled models (e.g., related to carbon cycle-climate feedbacks)[42,44,139–142]. 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 to the spread in output within a model ensemble.

Data assimilation techniques can bridge the gap between data availability and model requirements. In particular, inverse modelling such as Approximate Bayesian Computation use a wide range of data to refine values of input parameters[143–146]. 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[147], tree size distribution derived from inventory data[148] or remote-sensing products[149].

A promising avenue in terms of data assimilation is the spectrometry imagery of functional diversity[84,150], 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 standardisation (corrections and inter-calibration of remote sensing images) and methods for data extraction[151]. It also raises the issue that the input data themselves often derive from modelled products. For example, in modelling 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)[152].

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[153,154]. 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[155] at global scale levels. However, regional integrated assessment models 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 in order to facilitate data flows across systems[37,134]. 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. (2015)[154] combined formal numerical approaches, modeller 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 modeller 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 modeller confidence. Several other factors such as the quality and availability of validation data, the meta-modelling process, trust between modellers, derivation methods, and pragmatic factors such as time, resources, skills and experience were also found to be important[154].

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[156]. In the majority of cases, modelling 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[157]. 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[154]. 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[134]. Structured sensitivity analysis (also referred to as scenario-neutral approaches and impact response

surfaces) is valuable in evaluating whether the emergent behaviour 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 criticised [158]. 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[159].

Uncertainties in decision-making and decision-making methods

Overview of the 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.

In spite of 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[160]. Decision making is often disorganised and politicised, and has to deal with many trade-offs, as well as co-benefits, making it difficult to generalise about how uncertainty in scenarios and models affects decision making processes. While there is a significant body of work in decision theory and operations research on dealing with epistemic uncertainty in decision making, the lack of understanding of the relationship between science and the social and political processes of decision-making makes this 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. Controllability tends to be higher at local and national scales relative to regional and global scales[161]. 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[162]. In situations where controllability is low and uncertainty is high, robustness analysis[163] in support of scenario planning[164] may be favoured[165].

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 in scenarios and models 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, formalised uncertainty language is used to communicate levels of confidence in the assessment of scientific evidence[166], 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[167], 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[168], species richness[169], extinction risk[170], monetary value of ecosystem services[171].

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[172], or in the same strength of the signal-to-noise ratio[171]. 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)[173]. International initiatives such as GEOBON (https://geobon.org), GOOS (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[97,99], but the performance of indicators in capturing changes and associated uncertainty has rarely been tested in a systematic way[174,175].

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 different decision-making tools can, or cannot, address uncertainties in scenarios and models

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).

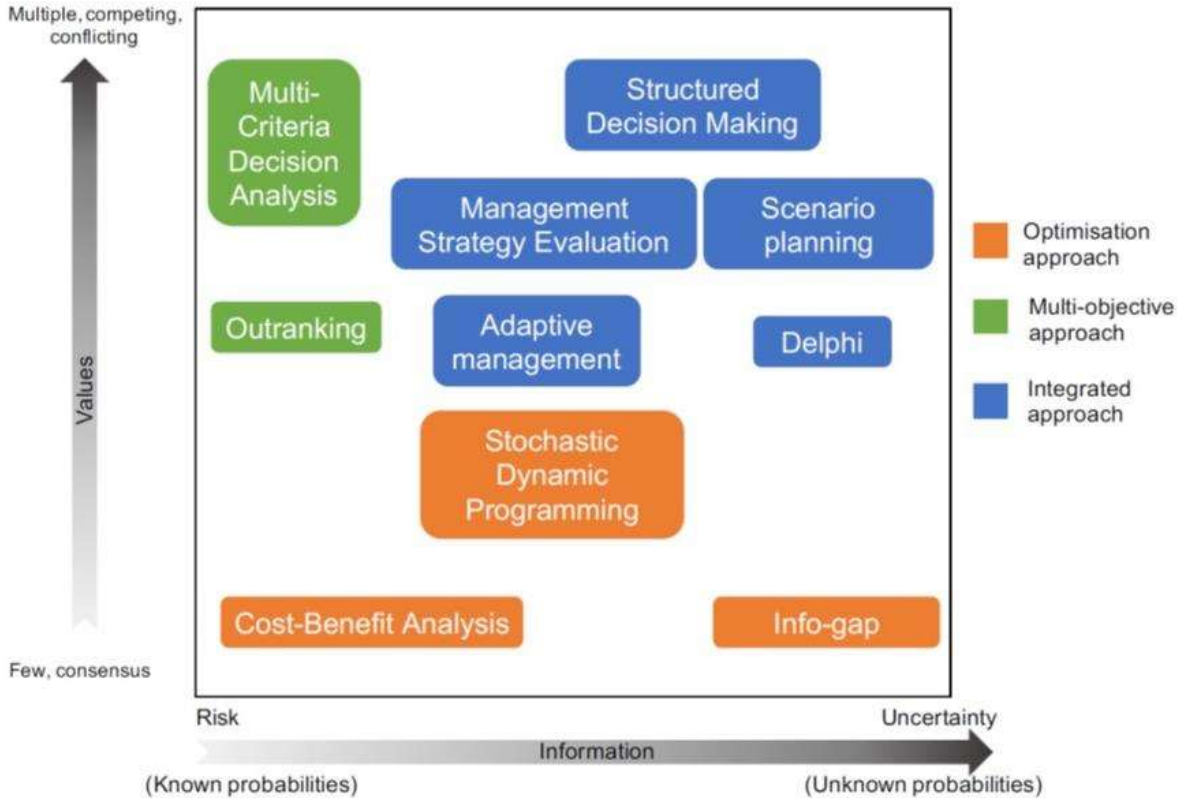


Figure 2. A sample of decision tools to support decision making in the presence of competing values and uncertainty. See Table 2 for tool summaries and key references. Optimisation approaches (orange) are a broad family of approaches that utilise either simple (cost benefit) or more sophisticated (info-gap) mathematical formulations that maximise an objective function. Multi-objective approaches (green) focus more on characterising 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).

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 summarised in Table 2.

In spite of 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, to limit and render comparable the broad, diverse range of services in question [176–179]. This implicitly involves the same value-based judgement 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[180,181]. This also contributes to the neglect of cultural services, and their uncertainties, in ecosystem services assessments[182]. 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[176].

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[183]. Comprehensive uncertainty evaluation can play an important role in this process[184], 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[185].

Table 2. Description of different decision support tools as presented in Figure 2.

Cost-benefit analysis (CBA), or benefit-cost analysis[186]	Applicable if all expected consequences of a decision are assigned a monetary value. Uncertainty can be partially addressed by computing expected benefit cost ratios that explicitly incorporate probabilities of benefits and costs, providing bounds around cost-benefit ratios, and analysing the sensitivity of the CBA ranking of options by systematically varying costs and benefits of each option within plausible bounds and exploring how these uncertainties impact on the ranking of options.
Multi criteria decision analysis (MCDA)[187]	Analyses trade-offs between decision options according to multiple objectives (criteria) by explicitly separating the tasks of causal judgment and value judgment.
Outranking	Designed for complex choice problems with multiple criteria and multiple participants. Out-ranking indicates the degree of dominance of one alternative over another. The outranking methods enable the utilisation of incomplete value information and judgments about the likelihood of outcomes.
Stochastic dynamic programming (SDP)[188]	finds optimal sequences of decisions under uncertainty. It is particularly useful in sequential decision problem to identify the optimal decision to take now, knowing that future decisions will adapt to future conditions. For that reason, SDP has been used in several **Adaptive Management** decision problems. Whilst these methods will work well within the uncertainty of a single scenario, there are doubts about whether they can meaningfully find an optimal solution across multiple, uncertain scenarios. For example, it has been argued that "*optimal adaptation is not a good representation of the*

	past, and probably is not a good representation of the future, because social and political constraints get in the way"[155]; constraints that are likely to be significant across the scenario space[189].
Structured Decision Making (SDM)[190]	An integrative decision-making framework that sets out a deliberative process for identifying acceptable trade-offs in complex decision problems. SDM is considered integrative because it often embeds other relatively simple tools such as MCDA in stakeholder consultation processes that may utilise sophisticated, model-based predictions of benefit of different decision options.
Management strategy evaluation (MSE)[162]	A modelling framework for assessing by simulation the consequences of several management strategies and providing a ranking of them according to their ability to reach management objectives. Its efficiency to link model-based knowledge to decision-making relies on co-produced objectives, uncertainty, interpretation of outputs and ranking scenarios.
Delphi technique[191]	Used in decision support in political environments when decisions affect strong factions with opposing preferences. It emphasizes anonymity of judgments during multiple rounds of deliberation and elicitation.
Info-gap decision theory[163]	A methodology for supporting model-based decisions under severe uncertainty. It seeks to maximize robustness and opportuneness (upside of uncertainty) of decisions using three key components; an uncertainty model, a system model and an objective function (called a 'performance requirement'). Info-gap is interesting in that it is specifically focussed on uncertainty in decision making and hence the uncertainty modelling aspects of the framework are particularly strongly developed.

Scenario Planning[164]	A tool for exploring possible, probable and/or preferable futures, and identifying strategies or options that are robust to a range of possible situations. Unlike forecasting, which aims to accurately predict future events, the focus of scenario planning is to explore possible futures that may arise under different conditions and what those different futures might mean for current decisions.

Discussion: ways forward

It is important to recognise 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 3 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 3. 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.

Table 3. Potential solutions and recommendations to address uncertainty in models and scenarios of socio-ecological systems for different sources of uncertainty (see Table 1.) that are visually presented in Figure 3. This list does not preclude other relationships between solutions and uncertainty sources that may be feasible.

	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 Annex 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 behavioural processes in affecting ecological change				✓					

12. Learning from uncertainty to guide model improvement				✓					
13. Qualitative "common sense" tests, where independent validation data are lacking				✓	✓				
14. Hierarchical statistical modelling 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 modelling e.g. approximate Bayesian Computation					✓				
17. Error propagation analysis through, for example, qualitative methods, formal numerical approaches, modeller 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 standardise 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	✓								✓

A number of ways of dealing with uncertainty are still not routinely applied in scenario modelling 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 Turner et al. (2018)[192] 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 stylised scenarios of, for example, consumption patterns, to scenarios and models that account for the role of human behavioural 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[193]. 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[194].

Uncertainty is often seen as the problem whilst 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 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.

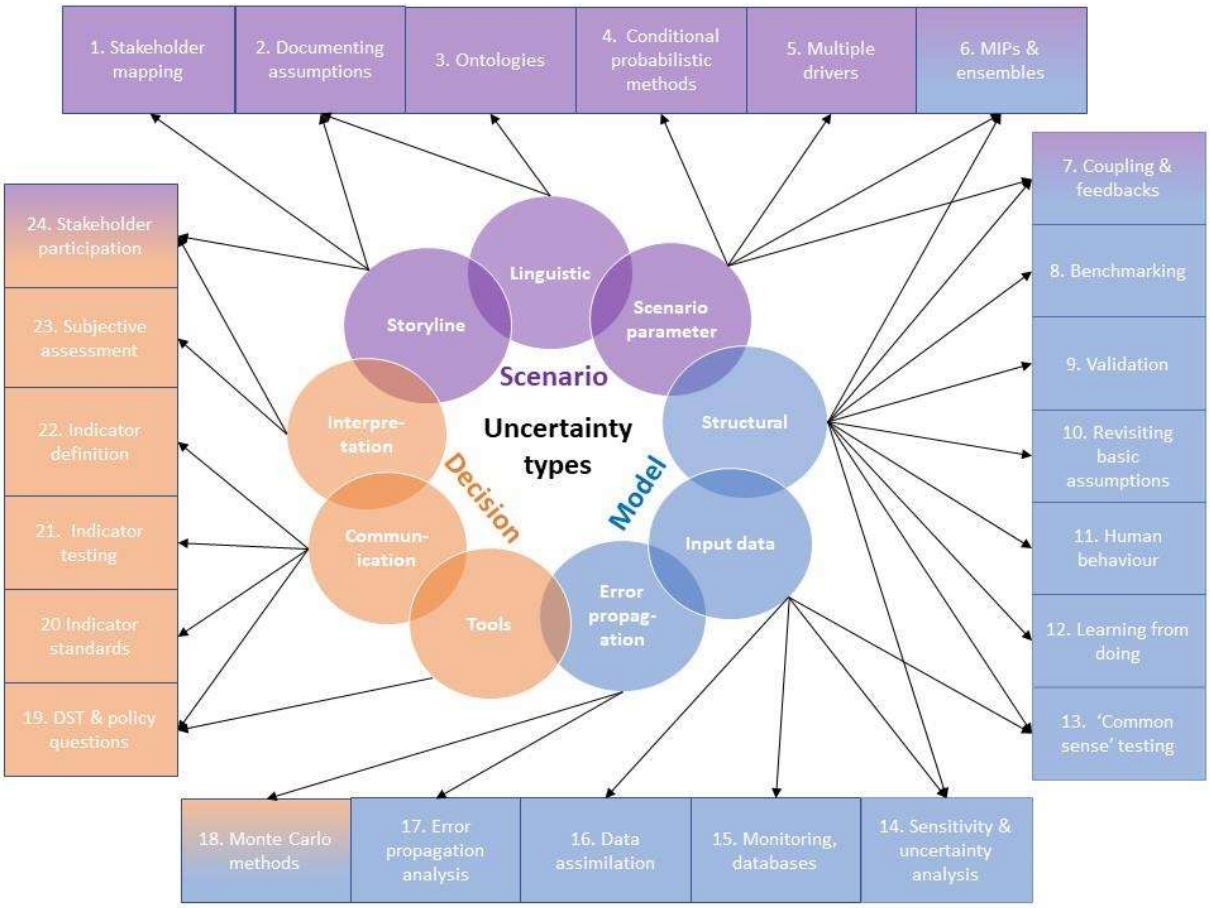


Figure 3. Visual summary of the types of uncertainties in scenarios and models of socio-ecological systems (categorised as scenario, model and decision uncertainties – see Table 1), and ways of addressing them. More details about the numbered methods for addressing uncertainties are provided

in Table 3. The colour-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.

Uncertainty in science should not imply uncertainty in making decisions that respond to environmental problems[195]. Ironically, scientists see the quantification of uncertainty as underpinning scientific rigour, whereas others see it as a sign of weakness in the underlying science[196]. 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[195].

Acknowledgements

This work is part of the USBIO project funded by the LabEx CeMEB (ANR-10-LABX-04-01). MR, AA and CB would like to acknowledge the funding of the Helmholtz Association. YJS was partly funded through the Biodiversa and Belmont Forum project SOMBEE (BiodivScen programme, ANR contract n°ANR-18-EBI4-0003-01). RP was partly funded by the FACCE Era-Gas project 3DForMod (ANR contract n°ANR-17-EGAS-0002-01). OG 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). WLC acknowledges funding support from NSERC Discovery Grant (RGPIN-2018-03864).

Author contributions

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

Declaration of interests

The authors declare no competing interests.

References

1. Russell, B. (1945). History of Western Philosophy (Simon & Schuster).

2. IPBES (2018). Biodiversity and Ecosystem Services for Europe and Central Asia (Secretariat of the Intergovernmental Science-Policy Platform for Biodiversity and Ecosystem Services. Bonn, Germany.).

3. Ferrier, S., Ninan, K.N., Leadley, P., Alkemade, R., Acosta, L.A., Akçakaya, H.R., Brotons, L., Cheung, W., Christensen, V., Harhash, K.A., et al. (2016). IPBES (2016): The Methodological Assessment Report on Scenarios and Models of Biodiversity and Ecosystem Services. Secretariat of the Intergovernmental Platform for Biodiversity and Ecosystem Services Bonn, Germany.

4. Millennium Ecosystem Assessment (2005). Ecosystems and Human Well-being: Biodiversity Synthesis (World Resources Institute).

5. Rounsevell, M.D.A., and Metzger, M.J. (2010). Developing qualitative scenario storylines for environmental change assessment. Wiley Interdisciplinary Reviews: Climate Change *1*, 606–619.

6. Acosta, L.A., Wintle, B.A., Benedek, Z., Chhetri, P.B., Heymans, S.J., Onur, A.C., Painter, R.L., Razafimpahanana, A., and Shoyama, K. (2016). The methodological assessment report on scenarios and models of biodiversity and ecosystem services. In, S. of the Intergovernmental Science-Policy Platform for Biodiversity and E. Services, eds., pp. 35–82.

7. Alexander, P., Prestele, R., Verburg, P.H., Arneth, A., Baranzelli, C., Batista e Silva, F., Brown, C., Butler, A., Calvin, K., Dendoncker, N., et al. (2017). Assessing uncertainties in land cover projections. Global Change Biology *23*, 767–781.

8. Brown, C., Seo, B., and Rounsevell, M. (2019). Societal breakdown as an emergent property of large-scale behavioural models of land use change. Earth System Dynamics *10*, 809–845.

9. Tittensor, D.P., Eddy, T.D., Lotze, H.K., Galbraith, E.D., Cheung, W., Barange, M., Blanchard, J.L., Bopp, L., Bryndum-Buchholz, A., Büchner, M., et al. (2018). A protocol for the intercomparison of marine fishery and ecosystem models: Fish-MIP v1.0. Geoscientific Model Development *11*, 1421–1442.

10. Travers, M., Shin, Y.J., Jennings, S., and Cury, P. (2007). Towards end-to-end models for investigating the effects of climate and fishing in marine ecosystems. Progress in Oceanography *75*, 751–770.

11. Harfoot, M.B.J., Newbold, T., Tittensor, D.P., Emmott, S., Hutton, J., Lyutsarev, V., Smith, M.J., Scharlemann, J.P.W., and Purves, D.W. (2014). Emergent Global Patterns of Ecosystem Structure and Function from a Mechanistic General Ecosystem Model. PLoS Biology *12*.

12. Pavlick, R., Drewry, D.T., Bohn, K., Reu, B., and Kleidon, A. (2013). The Jena Diversity-Dynamic Global Vegetation Model (JeDi-DGVM): a diverse approach to representing terrestrial biogeography and biogeochemistry based on plant functional trade-offs. Biogeosciences *10*, 4137–4177.

13. Prentice, I.C., Bondeau, A., Cramer, W., Harrison, S.P., Hickler, T., Lucht, W., Sitch, S., Smith, B., and Sykes, M.T. (2007). Dynamic Global Vegetation Modeling: Quantifying Terrestrial Ecosystem Responses to Large-Scale Environmental Change. In Terrestrial Ecosystems in a Changing World (Springer Berlin Heidelberg), pp. 175–192.

14. Daniel, C.J., Frid, L., and Sleeter, B.M. (2016). State-and-transition simulation models : a framework for forecasting landscape change. 1413–1423.

15. Buisson, L., Thuiller, W., Casajus, N., Lek, S., and Grenouillet, G. (2010). Uncertainty in ensemble forecasting of species distribution. Global Change Biology.

16. Medlyn, B.E., De Kauwe, M.G., Zaehle, S., Walker, A.P., Duursma, R.A., Luus, K., Mishurov, M., Pak, B., Smith, B., Wang, Y.-P., et al. (2016). Using models to guide field experiments: *a priori* predictions for the CO_2 response of a nutrient- and water-limited native Eucalypt woodland. Global Change Biology *22*, 2834–2851.

17. Cury, P.M., Shin, Y.J., Planque, B., Durant, J.M., Fromentin, J.M., Kramer-Schadt, S., Stenseth, N.C., Travers, M., and Grimm, V. (2008). Ecosystem oceanography for global change in fisheries. Trends in Ecology and Evolution *23*, 338–346.

18. Pereira, H.M., Leadley, P.W., Proença, V., Alkemade, R., Scharlemann, J.P.W., Fernandez-Manjarrés, J.F., Araújo, M.B., Balvanera, P., Biggs, R., Cheung, W.W.L., et al. (2010). Scenarios for global biodiversity in the 21st century. Science *330*, 1496–1501.

19. Elsawah, S., Hamilton, S.H., Jakeman, A.J., Rothman, D., Schweizer, V., Trutnevyte, E., Carlsen, H., Drakes, C., Frame, B., Fu, B., et al. (2020). Science of the Total Environment Scenario processes for socio-environmental systems analysis of futures : A review of recent efforts and a salient research

agenda for supporting decision making. *729*.

20. Regan, H.M., Colyvan, M., and Burgman, M.A. (2002). A taxonomy and treatment of uncertainty for ecology and conservation biology. Ecological applications *12*, 618–628.

21. O'Neill, B.C., Kriegler, E., Riahi, K., Ebi, K.L., Hallegatte, S., Carter, T.R., Mathur, R., and van Vuuren, D.P. (2014). A new scenario framework for climate change research: The concept of shared socioeconomic pathways. Climatic Change *122*, 387–400.

22. Madin, J.S., Bowers, S., Schildhauer, M.P., and Jones, M.B. (2008). Advancing ecological research with ontologies. Trends in ecology & evolution *23*, 159–168.

23. Sleeman, J., Finin, T., and Halem, M. (2018). Ontology-Grounded Topic Modeling for Climate Science Research. arXiv preprint arXiv:180710965.

24. van Vuuren, D.P., Kriegler, E., O'Neill, B.C., Ebi, K.L., Riahi, K., Carter, T.R., Edmonds, J., Hallegatte, S., Kram, T., Mathur, R., et al. (2014). A new scenario framework for Climate Change Research: scenario matrix architecture. Climatic Change *122*, 373–386.

25. Metzger, M.J., Schröter, D., Leemans, R., and Cramer, W. (2008). A spatially explicit and quantitative vulnerability assessment of ecosystem service change in Europe. Regional Environmental Change *8*, 91–107.

26. Maier, H.R., Guillaume, J.H.A., van Delden, H., Riddell, G.A., Haasnoot, M., and Kwakkel, J.H. (2016). An uncertain future, deep uncertainty, scenarios, robustness and adaptation: How do they fit together? Environmental Modelling & Software *81*, 154–164.

27. Trutnevyte, E., Guivarch, C., Lempert, R., and Strachan, N. (2016). Reinvigorating the scenario technique to expand uncertainty consideration. Climatic Change *135*, 373–379.

28. Taleb, N.N. (2007). The black swan: The impact of the highly improbable (Random house).

29. Metzger, M.J., Rounsevell, M.D.A., den Heiligenberg, H.A.R.M., Pérez-Soba, M., and Hardiman, P.S. (2010). How personal judgment influences scenario development: an example for future rural development in Europe. Ecology and Society *15*.

30. Henry, R.C., Alexander, P., Rabin, S., Anthoni, P., Rounsevell, M.D.A., and Arneth, A. (2019). The role of global dietary transitions for safeguarding biodiversity. Global Environmental Change *58*, 101956.

31. Vuuren, D.P. Van, Stehfest, E., Gernaat, D.E.H.J., Berg, M. Van Den, Bijl, D.L., Boer, H.S. De, Daioglou, V., Doelman, J.C., Edelenbosch, O.Y., Harmsen, M., et al. (2018). the need for negative emission technologies. Nature Climate Change *8*.

32. Brown, C., Alexander, P., Arneth, A., Holman, I., and Rounsevell, M. (2019). Achievement of Paris climate goals unlikely due to time lags in the land system. Nature Climate Change.

33. Lotze, H.K., Tittensor, D.P., Bryndum-Buchholz, A., Eddy, T.D., Cheung, W.W.L., Galbraith, E.D., Barange, M., Barrier, N., Bianchi, D., Blanchard, J.L., et al. (2019). Global ensemble projections reveal trophic amplification of ocean biomass declines with climate change. Proceedings of the National Academy of Sciences *116*, 12907–12912.

34. Gaines, S.D., Costello, C., Owashi, B., Mangin, T., Bone, J., Molinos, J.G., Burden, M., Dennis, H., Halpern, B.S., Kappel, C. V, et al. (2018). Improved fisheries management could offset many negative effects of climate change. Science Advances *4*, 1–9.

35. Dueri, S., Guillotreau, P., Jiménez-Toribio, R., Oliveros Ramos, R., Bopp, L., and Maury, O. (2016). Food security, biomass conservation or economic profitability? Projecting the effects of climate and socio-economic changes on the global skipjack tuna fisheries under various management strategies. Global Environmental Change *41*, 1–12.

36. Maury, O., Campling, L., Arrizabalaga, H., Aumont, O., Bopp, L., Merino, G., Squires, D., Cheung, W., Goujon, M., Guivarch, C., et al. (2017). From shared socio-economic pathways (SSPs) to oceanic system pathways (OSPs): Building policy-relevant scenarios for global oceanic ecosystems and fisheries. Global Environmental Change *45*, 203–216.

37. Harrison, P.A., Dunford, R.W., Holman, I.P., and Rounsevell, M.D.A. (2016). Climate change impact modelling needs to include cross-sectoral interactions. Nature Climate Change *6*, 885–890.

38. Kok, K., Bärlund, I., Flörke, M., Holman, I., Gramberger, M., Sendzimir, J., Stuch, B., and Zellmer, K. (2014). European participatory scenario development: strengthening the link between stories and models. Climatic Change *128*, 187–200.

39. Planque, B., Mullon, C., Arneberg, P., Eide, A., Fromentin, J.M., Heymans, J.J., Hoel, A.H., Niiranen, S., Ottersen, G., Sandø, A.B., et al. (2019). A participatory scenario method to explore the future of marine

social-ecological systems. Fish and Fisheries *20*, 434–451.

40. Gopnik, M., Fieseler, C., Cantral, L., McClellan, K., Pendleton, L., and Crowder, L. (2012). Coming to the table: Early stakeholder engagement in marine spatial planning. Marine Policy *36*, 1139–1149.

41. Pedde, S., Kok, K., Onigkeit, J., Brown, C., Holman, I., and Harrison, P.A. (2019). Bridging uncertainty concepts across narratives and simulations in environmental scenarios. Regional environmental change *19*, 655–666.

42. Henry, R.C., Engström, K., Olin, S., Alexander, P., Arneth, A., and Rounsevell, M.D.A. (2018). Food supply and bioenergy production within the global cropland planetary boundary. PLoS ONE *13*, 1–17.

43. Brown, C., Brown, E., Murray-Rust, D., Cojocaru, G., Savin, C., and Rounsevell, M. (2014). Analysing uncertainties in climate change impact assessment across sectors and scenarios. Climatic Change *128*, 293–306.

44. Engström, K., Olin, S., Rounsevell, M.D.A., Brogaard, S., Van Vuuren, D.P., Alexander, P., Murray-Rust, D., and Arneth, A. (2016). Assessing uncertainties in global cropland futures using a conditional probabilistic modelling framework. Earth System Dynamics *7*, 893–915.

45. Beulke, S., Brown, C.D., Dubus, I.G., Galicia, H., Jarvis, N., Schaefer, D., and Trevisan, M. (2006). User subjectivity in Monte Carlo modeling of pesticide exposure. Environmental Toxicology and Chemistry: An International Journal *25*, 2227–2236.

46. Costello, C., Ovando, D., Clavelle, T., Strauss, C.K., Hilborn, R., Melnychuk, M.C., Branch, T.A., Gaines, S.D., Szuwalski, C.S., Cabral, R.B., et al. (2016). Global fishery prospects under contrasting management regimes. Proceedings of the National Academy of Sciences *113*, 5125–5129.

47. Rousseau, Y., Watson, R.A., Blanchard, J.L., and Fulton, E.A. (2019). Evolution of global marine fishing fleets and the response of fished resources. Proceedings of the National Academy of Sciences *In press*.

48. Holman, I.P., Brown, C., Carter, T.R., Harrison, P.A., and Rounsevell, M. (2019). Improving the representation of adaptation in climate change impact models. Regional environmental change *19*, 711–721.

49. Levins, R. (1966). The strategy of model building in population biology. American scientist *54*, 421–431.

50. Prentice, I.C., Liang, X., Medlyn, B.E., and Wang, Y.-P. (2015). Reliable, robust and realistic: the three R's

of next-generation land-surface modelling. Atmospheric Chemistry and Physics *15*, 5987–6005.

51. Evans, M.R., Grimm, V., Johst, K., Knuuttila, T., de Langhe, R., Lessells, C.M., Merz, M., O'Malley, M.A., Orzack, S.H., Weisberg, M., et al. (2013). Do simple models lead to generality in ecology? Trends in Ecology & Evolution *28*, 578–583.

52. Yatat, V., Tchuinté, A., Dumont, Y., and Couteron, P. (2018). A tribute to the use of minimalistic spatially-implicit models of savanna vegetation dynamics to address broad spatial scales in spite of scarce data. Biomath *7*, 1812167.

53. Cheaib, A., Badeau, V., Boe, J., Chuine, I., Delire, C., Dufrêne, E., François, C., Gritti, E.S., Legay, M., Pagé, C., et al. (2012). Climate change impacts on tree ranges: model intercomparison facilitates understanding and quantification of uncertainty. Ecology Letters *15*, 533–544.

54. Bugmann, H., Seidl, R., Hartig, F., Bohn, F., Brůna, J., Cailleret, M., François, L., Heinke, J., Henrot, A.J., Hickler, T., et al. (2019). Tree mortality submodels drive simulated long-term forest dynamics: assessing 15 models from the stand to global scale. Ecosphere *10*.

55. De Weirdt, M., Verbeeck, H., Maignan, F., Peylin, P., Poulter, B., Bonal, D., Ciais, P., and Steppe, K. (2012). Seasonal leaf dynamics for tropical evergreen forests in a process-based global ecosystem model. Geoscientific Model Development *5*, 1091–1108.

56. Robinson, D.T., Di Vittorio, A., Alexander, P., Arneth, A., Michael Barton, C., Brown, D.G., Kettner, A., Lemmen, C., O'Neill, B.C., Janssen, M., et al. (2018). Modelling feedbacks between human and natural processes in the land system. Earth System Dynamics *9*, 895–914.

57. Xu, X., Medvigy, D., Powers, J.S., Becknell, J.M., and Guan, K. (2016). Diversity in plant hydraulic traits explains seasonal and inter-annual variations of vegetation dynamics in seasonally dry tropical forests. The New phytologist *212*, 80–95.

58. Fisher, R.A., Koven, C.D., Anderegg, W.R.L., Christoffersen, B.O., Dietze, M.C., Farrior, C.E., Holm, J.A., Hurtt, G.C., Knox, R.G., Lawrence, P.J., et al. (2018). Vegetation demographics in Earth System Models: A review of progress and priorities. Global Change Biology *24*, 35–54.

59. Moorcroft, P.R. (2006). How close are we to a predictive science of the biosphere? Trends in Ecology & Evolution *21*, 400–407.

60. Purves, D., and Pacala, S. (2008). Predictive models of forest dynamics. Science *320*, 1452–1453.

61. Sakschewski, B., von Bloh, W., Boit, A., Rammig, A., Kattge, J., Poorter, L., Peñuelas, J., and Thonicke, K. (2015). Leaf and stem economics spectra drive diversity of functional plant traits in a dynamic global vegetation model. Global Change Biology.

62. Pavlick, R., Drewry, D.T., Bohn, K., Reu, B., and Kleidon, A. (2013). The Jena Diversity-Dynamic Global Vegetation Model (JeDi-DGVM): a diverse approach to representing terrestrial biogeography and biogeochemistry based on plant functional trade-offs. Biogeosciences.

63. Maréchaux, I., and Chave, J. (2017). An individual-based forest model to jointly simulate carbon and tree diversity in Amazonia: description and applications. Ecological Monographs.

64. Van Bodegom, P.M., Douma, J.C., Witte, J.P.M., Ordoñez, J.C., Bartholomeus, R.P., and Aerts, R. (2012). Going beyond limitations of plant functional types when predicting global ecosystem-atmosphere fluxes: Exploring the merits of traits-based approaches. Global Ecology and Biogeography.

65. Mokany, K., Ferrier, S., Connolly, S.R., Dunstan, P.K., Fulton, E.A., Harfoot, M.B., Harwood, T.D., Richardson, A.J., Roxburgh, S.H., Scharlemann, J.P.W., et al. (2016). Integrating modelling of biodiversity composition and ecosystem function. Oikos *125*, 10–19.

66. Sakschewski, B., Von Bloh, W., Boit, A., Poorter, L., Peña-Claros, M., Heinke, J., Joshi, J., and Thonicke, K. (2016). Resilience of Amazon forests emerges from plant trait diversity. Nature Climate Change *6*, 1032–1036.

67. Voinov, A., and Shugart, H.H. (2013). 'Integronsters'', integral and integrated modeling.' Environmental Modelling & Software *39*, 149–158.

68. Jarnevich, C.S., Cullinane Thomas, C., Young, N.E., Backer, D., Cline, S., Frid, L., and Grissom, P. (2019). Developing an expert elicited simulation model to evaluate invasive species and fire management alternatives. Ecosphere *10*.

69. Holman, I.P., Brown, C., Carter, T.R., Harrison, P.A., and Rounsevell, M. (2018). Improving the representation of adaptation in climate change impact models. Regional Environmental Change, 1–11.

70. Brown, C., Alexander, P., Holzhauer, S., and Rounsevell, M.D.A. (2017). Behavioral models of climate change adaptation and mitigation in land-based sectors. Wiley Interdisciplinary Reviews: Climate

Change *8*, e448.

71. Van Nes, E.H., and Scheffer, M. (2005). A strategy to improve the contribution of complex simulation models to ecological theory. Ecological Modelling *185*, 153–164.

72. De Weirdt, M., Verbeeck, H., Maignan, F., Peylin, P., Poulter, B., Bonal, D., Ciais, P., and Steppe, K. (2012). Seasonal leaf dynamics for tropical evergreen forests in a process-based global ecosystem model. Geoscientific Model Development *5*, 1091–1108.

73. Joetzjer, E., Pillet, M., Ciais, P., Barbier, N., Chave, J., Schlund, M., Maignan, F., Barichivich, J., Luyssaert, S., Hérault, B., et al. (2017). Assimilating satellite-based canopy height within an ecosystem model to estimate aboveground forest biomass. Geophysical Research Letters.

74. Naudts, K., Ryder, J., McGrath, M.J., Otto, J., Chen, Y., Valade, A., Bellasen, V., Berhongaray, G., Bönisch, G., Campioli, M., et al. (2015). A vertically discretised canopy description for ORCHIDEE (SVN r2290) and the modifications to the energy, water and carbon fluxes. Geoscientific Model Development *8*, 2035–2065.

75. Kim, H., Rosa, I.M.D., Alkemade, R., Leadley, P., Hurtt, G., Popp, A., Anthoni, P., Arneth, A., Baisero, D., Caton, E., et al. (2018). A protocol for an intercomparison of biodiversity and ecosystem services models using harmonized land-use and climate scenarios. 1–37.

76. Rounsevell, M.D.A., Arneth, A., Alexander, P., Brown, D.G., de Noblet-Ducoudré, N., Ellis, E., Finnigan, J., Galvin, K., Grigg, N., Harman, I., et al. (2014). Towards decision-based global land use models for improved understanding of the Earth system. Earth System Dynamics *5*, 117–137.

77. Cheaib, A., Badeau, V., Boe, J., Chuine, I., Delire, C., Dufrêne, E., François, C., Gritti, E.S., Legay, M., Pagé, C., et al. (2012). Climate change impacts on tree ranges: model intercomparison facilitates understanding and quantification of uncertainty. Ecology Letters *15*, 533–544.

78. Powell, T.L., Galbraith, D.R., Christoffersen, B.O., Harper, A., Imbuzeiro, H.M.A., Rowland, L., Almeida, S., Brando, P.M., da Costa, A.C.L., Costa, M.H., et al. (2013). Confronting model predictions of carbon fluxes with measurements of Amazon forests subjected to experimental drought. New Phytologist *200*, 350–365.

79. Restrepo-Coupe, N., Levine, N.M., Christoffersen, B.O., Albert, L.P., Wu, J., Costa, M.H., Galbraith, D.,

Imbuzeiro, H., Martins, G., da Araujo, A.C., et al. (2017). Do dynamic global vegetation models capture the seasonality of carbon fluxes in the Amazon basin? A data-model intercomparison. Global Change Biology *23*, 191–208.

80. Taylor, K.E., Stouffer, R.J., and Meehl, G.A. (2012). An overview of CMIP5 and the experiment design. Bulletin of the American Meteorological Society *93*, 485–498.

81. Tittensor, D.P., Walpole, M., Hill, S.L.L., Boyce, D.G., Britten, G.L., Burgess, N.D., Butchart, S.H.M., Leadley, P.W., Regan, E.C., Alkemade, R., et al. (2014). A mid-term analysis of progress toward international biodiversity targets. Science *346*, 241–244.

82. Mouquet, N., Lagadeuc, Y., Devictor, V., Doyen, L., Duputié, A., Eveillard, D., Faure, D., Garnier, E., Gimenez, O., Huneman, P., et al. (2015). Predictive ecology in a changing world. Journal of Applied Ecology.

83. Kelley, D.I., Prentice, I.C., Harrison, S.P., Wang, H., Simard, M., Fisher, J.B., and Willis, K.O. (2013). A comprehensive benchmarking system for evaluating global vegetation models. Biogeosciences *10*, 3313–3340.

84. Asner, G.P., Martin, R.E., Knapp, D.E., Tupayachi, R., Anderson, C.B., Sinca, F., Vaughn, N.R., and Llactayo, W. (2017). Airborne laser-guided imaging spectroscopy to map forest trait diversity and guide conservation. Science.

85. Tanentzap, A.J., and Coomes, D.A. (2012). Carbon storage in terrestrial ecosystems: do browsing and grazing herbivores matter? Biological Reviews *87*, 72–94.

86. Walker, A.P., Zaehle, S., Medlyn, B.E., De Kauwe, M.G., Asao, S., Hickler, T., Parton, W., Ricciuto, D.M., Wang, Y.-P., Wårlind, D., et al. (2015). Predicting long-term carbon sequestration in response to CO2 enrichment: How and why do current ecosystem models differ? Global Biogeochemical Cycles *29*, 476–495.

87. Beven, K., and Freer, J. (2001). Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology. Journal of Hydrology *249*, 11–29.

88. Luo, Y., Weng, E., Wu, X., Gao, C., Zhou, X., and Zhang, L. (2009). Parameter identifiability, constraint,

and equifinality in data assimilation with ecosystem models. Ecological Applications *19*, 571–574.

89. Rykiel, E.J. (1996). Testing ecological models: the meaning of validation. Ecological Modelling *90*, 229–244.

90. Medlyn, B.E., Robinson, A.P., Clement, R., and McMurtrie, R.E. (2005). On the validation of models of forest CO2 exchange using eddy covariance data: some perils and pitfalls. Tree Physiology *25*, 839–857.

91. van Vliet, J., Bregt, A.K., Brown, D.G., van Delden, H., Heckbert, S., and Verburg, P.H. (2016). A review of current calibration and validation practices in land-change modeling. Environmental Modelling & Software *82*, 174–182.

92. Remesan, R., and Holman, I.P. (2015). Effect of baseline meteorological data selection on hydrological modelling of climate change scenarios. Journal of Hydrology *528*, 631–642.

93. Remesan, R., Begam, S., and Holman, I.P. (2019). Effect of baseline snowpack assumptions in the HySIM model in predicting future hydrological behaviour of a Himalayan catchment. Hydrology Research *50*, 691–708.

94. Prestele, R., Alexander, P., Rounsevell, M.D.A., Arneth, A., Calvin, K., Doelman, J., Eitelberg, D.A., Engström, K., Fujimori, S., Hasegawa, T., et al. (2016). Hotspots of uncertainty in land-use and land-cover change projections: a global-scale model comparison. Global Change Biology.

95. Urban, M.C., Bocedi, G., Hendry, A.P., Mihoub, J.B., Pe'er, G., Singer, A., Bridle, J.R., Crozier, L.G., De Meester, L., Godsoe, W., et al. (2016). Improving the forecast for biodiversity under climate change. Science *353*.

96. Gillespie, T.W., Foody, G.M., Rocchini, D., Giorgi, A.P., and Saatchi, S. (2008). Measuring and modelling biodiversity from space. Progress in Physical Geography.

97. Pereira, H.M., Ferrier, S., Walters, M., Geller, G.N., Jongman, R.H.G., Scholes, R.J., Bruford, M.W., Brummitt, N., Butchart, S.H.M., Cardoso, A.C., et al. (2013). Essential biodiversity variables. Science.

98. Muller-Karger, F.E., Miloslavich, P., Bax, N.J., Simmons, S., Costello, M.J., Sousa Pinto, I., Canonico, G., Turner, W., Gill, M., Montes, E., et al. (2018). Advancing Marine Biological Observations and Data Requirements of the Complementary Essential Ocean Variables (EOVs) and Essential Biodiversity Variables (EBVs) Frameworks. Frontiers in Marine Science *5*, 1–15.

99. Miloslavich, P., Bax, N.J., Simmons, S.E., Klein, E., Appeltans, W., Aburto-Oropeza, O., Andersen Garcia, M., Batten, S.D., Benedetti-Cecchi, L., Checkley, D.M., et al. (2018). Essential ocean variables for global sustained observations of biodiversity and ecosystem changes. Global Change Biology *24*, 2416–2433.

100. Affouard, A., Goëau, H., Bonnet, P., Lombardo, J.-C., Joly, A., and Goeau, H. (2017). Pl@ntNet app in the era of deep learning.

101. Delbart, N., Beaubien, E., Kergoat, L., and Le Toan, T. (2015). Comparing land surface phenology with leafing and flowering observations from the PlantWatch citizen network. Remote Sensing of Environment.

102. Giraud, C., Calenge, C., Coron, C., and Julliard, R. (2016). Capitalizing on opportunistic data for monitoring relative abundances of species. Biometrics.

103. Elith, J., and Leathwick, J.R. (2009). Species Distribution Models: Ecological Explanation and Prediction Across Space and Time. Annual Review of Ecology, Evolution, and Systematics.

104. Guisan, A., and Thuiller, W. (2005). Predicting species distribution: Offering more than simple habitat models. Ecology Letters.

105. Buisson, L., Thuiller, W., Casajus, N., Lek, S., and Grenouillet, G. (2010). Uncertainty in ensemble forecasting of species distribution. Global Change Biology *16*, 1145–1157.

106. Jiménez-Valverde, A., Lobo, J.M., and Hortal, J. (2008). Not as good as they seem: The importance of concepts in species distribution modelling. Diversity and Distributions.

107. Barry, S., and Elith, J. (2006). Error and uncertainty in habitat models. Journal of Applied Ecology.

108. Bean, W.T., Stafford, R., and Brashares, J.S. (2012). The effects of small sample size and sample bias on threshold selection and accuracy assessment of species distribution models. Ecography.

109. Lobo, J.M., Jiménez-Valverde, A., and Hortal, J. (2010). The uncertain nature of absences and their importance in species distribution modelling. Ecography.

110. Syfert, M.M., Smith, M.J., and Coomes, D.A. (2013). The Effects of Sampling Bias and Model Complexity on the Predictive Performance of MaxEnt Species Distribution Models. PLoS ONE.

111. Violle, C., Navas, M.-L., Vile, D., Kazakou, E., Fortunel, C., Hummel, I., and Garnier, E. (2007). Let the concept of trait be functional! Oikos *116*, 882–892.

112. Mar Echaux, I., Er, J., and Chave, ^ Ome (2017). An individual-based forest model to jointly simulate carbon and tree diversity in Amazonia: description and applications.

113. Pollock, L.J., Morris, W.K., and Vesk, P.A. (2012). The role of functional traits in species distributions revealed through a hierarchical model. Ecography *35*, 716–725.

114. Sakschewski, B., von Bloh, W., Boit, A., Rammig, A., Kattge, J., Poorter, L., Peñuelas, J., and Thonicke, K. (2015). Leaf and stem economics spectra drive diversity of functional plant traits in a dynamic global vegetation model. Global Change Biology *21*, 2711–2725.

115. Guiet, J., Aumont, O., Poggiale, J.C., and Maury, O. (2016). Effects of lower trophic level biomass and water temperature on fish communities: A modelling study. Progress in Oceanography *146*, 22–37.

116. Blanchard, J.L., Jennings, S., Holmes, R., Harle, J., Merino, G., Allen, J.I., Holt, J., Dulvy, N.K., and Barange, M. (2012). Potential consequences of climate change for primary production and fish production in large marine ecosystems. Phil Trans R Soc B *367*, 2979–2989.

117. Moullec, F., Velez, L., Verley, P., Barrier, N., Ulses, C., Carbonara, P., Esteban, A., Follesa, C., Gristina, M., Jadaud, A., et al. (2019). Progress in Oceanography Capturing the big picture of Mediterranean marine biodiversity with an end- to-end model of climate and fishing impacts. Progress in Oceanography *178*, 102179.

118. Allen, W.L., Street, S.E., and Capellini, I. (2017). Fast life history traits promote invasion success in amphibians and reptiles. Ecology Letters *20*, 222–230.

119. Parr, C.S., Wilson, N., Leary, P., Schulz, K., Lans, K., Walley, L., Hammock, J., Goddard, A., Rice, J., Studer, M., et al. (2014). The Encyclopedia of Life v2: Providing Global Access to Knowledge About Life on Earth. Biodiversity Data Journal *2*, e1079.

120. Kattge, J., Díaz, S., Lavorel, S., Prentice, I.C., Leadley, P., Bönisch, G., Garnier, E., Westoby, M., Reich, P.B., Wright, I.J., et al. (2011). TRY - a global database of plant traits. Global Change Biology.

121. Griffin-Nolan, R.J., Bushey, J.A., Carroll, C.J.W., Challis, A., Chieppa, J., Garbowski, M., Hoffman, A.M., Post, A.K., Slette, I.J., Spitzer, D., et al. (2018). Trait selection and community weighting are key to understanding ecosystem responses to changing precipitation regimes. Functional Ecology.

122. Paine, C.E.T., Deasey, A., and Duthie, A.B. (2018). Towards the general mechanistic prediction of

community dynamics. Functional Ecology.

123. Shipley, B., De Bello, F., Cornelissen, J.H.C., Laliberté, E., Laughlin, D.C., and Reich, P.B. (2016). Reinforcing loose foundation stones in trait-based plant ecology. Oecologia.

124. Adler, P.B., Smull, D., Beard, K.H., Choi, R.T., Furniss, T., Kulmatiski, A., Meiners, J.M., Tredennick, A.T., and Veblen, K.E. (2018). Competition and coexistence in plant communities: intraspecific competition is stronger than interspecific competition. Ecology Letters.

125. Albert, C.H., Grassein, F., Schurr, F.M., Vieilledent, G., and Violle, C. (2011). When and how should intraspecific variability be considered in trait-based plant ecology? Perspectives in Plant Ecology, Evolution and Systematics.

126. Bolnick, D.I., Amarasekare, P., Araújo, M.S., Bürger, R., Levine, J.M., Novak, M., Rudolf, V.H.W., Schreiber, S.J., Urban, M.C., and Vasseur, D.A. (2011). Why intraspecific trait variation matters in community ecology. Trends in Ecology and Evolution.

127. Clark, J.S., Dietze, M., Chakraborty, S., Agarwal, P.K., Ibanez, I., LaDeau, S., and Wolosin, M. (2007). Resolving the biodiversity paradox. Ecology Letters.

128. Kissling, W.D., Walls, R., Bowser, A., Jones, M.O., Kattge, J., Agosti, D., Amengual, J., Basset, A., van Bodegom, P.M., Cornelissen, J.H.C., et al. (2018). Towards global data products of Essential Biodiversity Variables on species traits. Nature Ecology and Evolution.

129. Payne, M.R., Barange, M., Cheung, W.W.L., MacKenzie, B.R., Batchelder, H.P., Cormon, X., Eddy, T.D., Fernandes, J.A., Hollowed, A.B., Jones, M.C., et al. (2015). Uncertainties in projecting climate-change impacts in marine ecosystems. ICES Journal of Marine Science *73*, 1272–1282.

130. Hurtt, G.C., Fisk, J., Thomas, R.Q., Dubayah, R., Moorcroft, P.R., and Shugart, H.H. (2010). Linking models and data on vegetation structure. Journal of Geophysical Research: Biogeosciences.

131. Rödig, E., Cuntz, M., Rammig, A., Fischer, R., Taubert, F., and Huth, A. (2018). The importance of forest structure for carbon fluxes of the Amazon rainforest. Environmental Research Letters.

132. Beale, C.M., and Lennon, J.J. (2012). Incorporating uncertainty in predictive species distribution modelling. Philosophical Transactions of the Royal Society B: Biological Sciences.

133. Clark, J.S. (2003). Uncertainty and variability in demography and population growth: a hierarchical

approach. Ecology *84*, 1370–1381.

134. Kebede, A.S., Dunford, R., Mokrech, M., Audsley, E., Harrison, P.A., Holman, I.P., Nicholls, R.J., Rickebusch, S., Rounsevell, M.D.A., Sabaté, S., et al. (2015). Direct and indirect impacts of climate and socio-economic change in Europe: a sensitivity analysis for key land- and water-based sectors. Climatic Change *128*, 261–277.

135. Pianosi, F., Beven, K., Freer, J., Hall, J.W., Rougier, J., Stephenson, D.B., and Wagener, T. (2016). Sensitivity analysis of environmental models: A systematic review with practical workflow. Environmental Modelling and Software.

136. Urban, M.C., Bocedi, G., Hendry, A.P., Mihoub, J.B., Pe'er, G., Singer, A., Bridle, J.R., Crozier, L.G., De Meester, L., Godsoe, W., et al. (2016). Improving the forecast for biodiversity under climate change. Science.

137. Williams, M., Richardson, A.D., Reichstein, M., Stoy, P.C., Peylin, P., Verbeeck, H., Carvalhais, N., Jung, M., Hollinger, D.Y., Kattge, J., et al. (2009). Improving land surface models with FLUXNET data. Biogeosciences.

138. Parker, W.S. (2013). Ensemble modeling, uncertainty and robust predictions. Wiley Interdisciplinary Reviews-Climate Change *4*, 213–223.

139. Booth, B.B.B., Jones, C.D., Collins, M., Totterdell, I.J., Cox, P.M., Sitch, S., Huntingford, C., Betts, R., Harris, G.R., and Lloyd, J. (2012). High sensitivity of future global warming to land carbon cycle uncertainties. Environmental Research Letters *7*, doi: 10.1088/1748-9326/7/2/024002.

140. Lienert, S., and Joos, F. (2018). A Bayesian ensemble data assimilation to constrain model parameters and land-use carbon emissions. Biogeosciences *15*, 2909–2930.

141. Wramneby, A., Smith, B., Zaehle, S., and Sykes, M.T. (2008). Parameter uncertainties in the modelling of vegetation dynamics - effects on tree community structure and ecosystem functioning in European forest biomes. Ecological Modelling *216*, 277–290.

142. Zaehle, S., Sitch, S., Smith, B., and Hatterman, F. (2005). Effects of parameter uncertainties on the modeling of terrestrial biosphere dynamics. Global Biogeochemical Cycles *19*, GB3020, doi:10.1029/2004GB002395.

143. Hartig, F., Dyke, J., Hickler, T., Higgins, S.I., O'Hara, R.B., Scheiter, S., and Huth, A. (2012). Connecting dynamic vegetation models to data - an inverse perspective. Journal of Biogeography.

144. Lagarrigues, G., Jabot, F., Lafond, V., and Courbaud, B. (2015). Approximate Bayesian computation to recalibrate individual-based models with population data: Illustration with a forest simulation model. Ecological Modelling.

145. LeBauer, D.S., Wang, D., Richter, K.T., Davidson, C.C., and Dietze, M.C. (2013). Facilitating feedbacks between field measurements and ecosystem models. Ecological Monographs.

146. Van Oijen, M., Rougier, J., and Smith, R. (2005). Bayesian calibration of process-based forest models: bridging the gap between models and data. Tree Physiology *25*, 915–927.

147. Baldocchi, D., Falge, E., Gu, L., Olson, R., Hollinger, D., Running, S., Anthoni, P., Bernhofer, C., Davis, K., Evans, R., et al. (2001). FLUXNET: A New Tool to Study the Temporal and Spatial Variability of Ecosystem-Scale Carbon Dioxide, Water Vapor, and Energy Flux Densities. Bulletin of the American Meteorological Society *82*.

148. Anderson-Teixeira, K.J., Davies, S.J., Bennett, A.C., Gonzalez-Akre, E.B., Muller-Landau, H.C., Joseph Wright, S., Abu Salim, K., Almeyda Zambrano, A.M., Alonso, A., Baltzer, J.L., et al. (2015). CTFS-ForestGEO: A worldwide network monitoring forests in an era of global change. Global Change Biology *21*, 528–549.

149. Fischer, F.J., Maréchaux, I., and Chave, J. (2019). Improving plant allometry by fusing forest models and remote sensing. New Phytologist.

150. Moreno-Martínez, Á., Camps-Valls, G., Kattge, J., Robinson, N., Reichstein, M., van Bodegom, P., Kramer, K., Cornelissen, J.H.C., Reich, P., Bahn, M., et al. (2018). A methodology to derive global maps of leaf traits using remote sensing and climate data. Remote Sensing of Environment.

151. Jucker, T., Caspersen, J., Chave, J., Antin, C., Barbier, N., Bongers, F., Dalponte, M., van Ewijk, K.Y., Forrester, D.I., Haeni, M., et al. (2017). Allometric equations for integrating remote sensing imagery into forest monitoring programmes. Global Change Biology.

152. Ahlström, A., Schurgers, G., Arneth, A., and Smith, B. (2012). Robustness and uncertainty in terrestrial ecosystem carbon response to CMIP5 climate change projections. Environmental Research Letters *7*,

44008.

153. Cheung, W.W.L., Frölicher, T.L., Asch, R.G., Jones, M.C., Pinsky, M.L., Reygondeau, G., Rodgers, K.B., Rykaczewski, R.R., Sarmiento, J.L., Stock, C., et al. (2016). Building confidence in projections of the responses of living marine resources to climate change. ICES Journal of Marine Science *73*, 1283–1296.

154. Dunford, R., Harrison, P.A., and Rounsevell, M.D.A. (2015). Exploring scenario and model uncertainty in cross-sectoral integrated assessment approaches to climate change impacts. Climatic Change *132*, 417–432.

155. Patt, A.G., van Vuuren, D.P., Berkhout, F., Aaheim, A., Hof, A.F., Isaac, M., and Mechler, R. (2010). Adaptation in integrated assessment modeling: where do we stand? Climatic Change *99*, 383–402.

156. Lo, E. (2005). Gaussian error propagation applied to ecological data: Post-ice-storm- downed woody biomass. Ecological Monographs.

157. Hilborn, R., and Mangel, M. (1997). The ecological detective : confronting models with data (Princeton University Press).

158. Saltelli, A., Aleksankina, K., Becker, W., Fennell, P., Ferretti, F., Holst, N., Li, S., and Wu, Q. (2019). Why so many published sensitivity analyses are false: A systematic review of sensitivity analysis practices. Environmental modelling & software *114*, 29–39.

159. Clark, J.S. (2005). Why environmental scientists are becoming Bayesians. Ecology Letters.

160. Brown, C., Alexander, P., Arneth, A., Holman, I., and Rounsevell, M. (2015). time lags in the land system. Nature Climate Change.

161. Low, S., and Schäfer, S. (2020). Energy Research & Social Science Is bio-energy carbon capture and storage (BECCS) feasible ? The contested authority of integrated assessment modeling. Energy Research & Social Science *60*, 101326.

162. Holland, D.S. (2010). Management Strategy Evaluation and Management Procedures: Tools for Rebuilding and Sustaining Fisheries. AbhatooNetMa, 66.

163. Regan, H.M., Ben-Haim, Y., Langford, B., Wilson, W.G., Lundberg, P., Andelman, S.J., and Burgman, M.A. (2005). Robust decision-making under severe uncertainty for conservation management. Ecological Applications *15*, 1471–1477.

164. Peterson, G.D., Cumming, G.S., and Carpenter, S.R. (2003). Scenario planning: A tool for conservation in an uncertain world. Conservation Biology *17*, 358–366.

165. Allen, C.R., Angeler, D.G., Fontaine, J.J., Garmestani, A.S., Hart, N.M., Pope, K.L., and Twidwell, D. (2017). Adaptive Management of Rangeland Systems. 373–394.

166. Helgeson, C., Bradley, R., and Hill, B. (2018). Combining probability with qualitative degree-of-certainty metrics in assessment. Climatic Change *149*, 517–525.

167. Bradley, R., Helgeson, C., and Hill, B. (2017). Climate change assessments: Confidence, probability, and decision. Philosophy of Science *84*, 500–522.

168. Visconti, P., Bakkenes, M., Baisero, D., Brooks, T., Butchart, S.H.M., Joppa, L., Alkemade, R., Di Marco, M., Santini, L., Hoffmann, M., et al. (2016). Projecting Global Biodiversity Indicators under Future Development Scenarios. Conservation Letters *9*, 5–13.

169. Beckmann, M., Gerstner, K., Akin-Fajiye, M., Ceauşu, S., Kambach, S., Kinlock, N.L., Phillips, H.R.P., Verhagen, W., Gurevitch, J., Klotz, S., et al. (2019). Land-use intensification effects on species richness and production: A global meta-analysis. Global Change Biology *(in press)*, 1–16.

170. Rounsevell, M.D.A., Harfoot, M., Harrison, P.A., Newbold, T., Gregory, R.D., and Mace, G.M. (2020). A biodiversity target based on species extinctions. Science (New York, NY) *368*, 1193–1195.

171. Shin, Y.-J., Houle, J.E., Akoglu, E., Blanchard, J.L., Bundy, A., Coll, M., Demarcq, H., Fu, C., Fulton, E.A., Heymans, J.J., et al. (2018). The specificity of marine ecological indicators to fishing in the face of environmental change: A multi-model evaluation. Ecological Indicators *89*, 317–326.

172. Lehuta Sigrid Mahevas Stephanie, L.F.P.P.P. (2013). A simulation-based approach to assess sensitivity and robustness of fisheries management indicators for the pelagic fishery in the Bay of Biscay. Canadian Journal Of Fisheries And Aquatic Sciences *70*, 1741–1756.

173. Schindler, D.E., Armstrong, J.B., and Reed, T.E. (2015). The portfolio concept in ecology and evolution. Frontiers in Ecology and the Environment *13*, 257–263.

174. Shin, Y.J., Bundy, A., Shannon, L.J., Blanchard, J.L., Chuenpagdee, R., Coll, M., Knight, B., Lynam, C., Piet, G., and Richardson, A.J. (2012). Global in scope and regionally rich: An IndiSeas workshop helps shape the future of marine ecosystem indicators. Reviews in Fish Biology and Fisheries *22*, 835–845.

175. Fu, C., Xu, Y., Bundy, A., Grüss, A., Coll, M., Heymans, J.J., Fulton, E.A., Shannon, L., Halouani, G., Velez, L., et al. (2019). Making ecological indicators management ready : Assessing the speci fi city , sensitivity , and threshold response of ecological indicators. *105*, 16–28.

176. Bagstad, K.J., Semmens, D.J., Waage, S., and Winthrop, R. (2013). A comparative assessment of decision-support tools for ecosystem services quantification and valuation. Ecosystem Services *5*, 27–39.

177. Schulp, C.J.E., Burkhard, B., Maes, J., Van Vliet, J., and Verburg, P.H. (2014). Uncertainties in ecosystem service maps: a comparison on the European scale. PloS one *9*.

178. Watkiss, P., Hunt, A., Blyth, W., and Dyszynski, J. (2015). The use of new economic decision support tools for adaptation assessment: A review of methods and applications, towards guidance on applicability. Climatic Change *132*, 401–416.

179. Wegner, G., and Pascual, U. (2011). Cost-benefit analysis in the context of ecosystem services for human well-being: A multidisciplinary critique. Global Environmental Change *21*, 492–504.

180. Minx, J.C., Callaghan, M., Lamb, W.F., Garard, J., and Edenhofer, O. (2017). Learning about climate change solutions in the IPCC and beyond. Environmental Science & Policy *77*, 252–259.

181. Watts, D.J. (2017). Should social science be more solution-oriented? Nature Human Behaviour *1*, 15.

182. Grêt-Regamey, A., Sirén, E., Brunner, S.H., and Weibel, B. (2017). Review of decision support tools to operationalize the ecosystem services concept. Ecosystem Services *26*, 306–315.

183. Daw, T.M., Coulthard, S., Cheung, W.W.L., Brown, K., Abunge, C., Galafassi, D., Peterson, G.D., McClanahan, T.R., Omukoto, J.O., and Munyi, L. (2015). Evaluating taboo trade-offs in ecosystems services and human well-being. Proceedings of the National Academy of Sciences *112*, 6949–6954.

184. Uusitalo, L., Lehikoinen, A., Helle, I., and Myrberg, K. (2015). An overview of methods to evaluate uncertainty of deterministic models in decision support. Environmental Modelling & Software *63*, 24–31.

185. Estévez, R.A., and Gelcich, S. (2015). Participative multi-criteria decision analysis in marine management and conservation: research progress and the challenge of integrating value judgments and uncertainty. Marine Policy *61*, 1–7.

186. Newcomer, B.K.E., Hatry, H.P., Wholey, J.S., Newcomer, K.E., Hatry, H.P., and Wholey, J.S. (2015). COST-BENEFIT ANALYSIS. 636–672.

187. Keeney, R.L., and Raiffa, H. (1979). Decisions with Multiple Objectives: Preferences and Value Trade-Offs. IEEE Transactions on Systems, Man and Cybernetics *9*, 403.

188. Mcdonald-madden, A.E., Probert, W.J.M., Hauser, C.E., Michael, C., Possingham, H.P., Jones, M.E., Moore, J.L., Rout, T.M., Peter, A., Wintle, B.A., et al. (2017). Active adaptive conservation of threatened species in the face of uncertainty Published by : Wiley on behalf of the Ecological Society of America Stable URL : http://www.jstor.org/stable/25680392 REFERENCES Linked references are available on JSTOR for thi. *20*, 1476–1489.

189. Chankong, V., and Haimes, Y.Y. (2008). Multiobjective Decision Making: Theory and Methodology (Dover Publications).

190. Gregory, R., Failing, L., Harstone, M., Long, G., McDaniels, T., and Ohlson, D. (2012). Structured Decision Making.

191. Rauch, W. (1979). The decision Delphi. Technological Forecasting and Social Change *15*, 159–169.

192. Turner, P.A., Field, C.B., Lobell, D.B., Sanchez, D.L., and Mach, K.J. (2018). Unprecedented rates of land-use transformation in modelled climate change mitigation pathways.

193. Larrosa, C., Carrasco, L.R., and Milner-Gulland, E.J. (2016). Unintended Feedbacks: Challenges and Opportunities for Improving Conservation Effectiveness. Conservation Letters *9*, 316–326.

194. Arneth, A, Olsson, L., Annette, A., Erb, K-H., Hurlbert, M., Kurz, W.A., Mirzabaev, A & Rounsevell, M.D.A. (2021). Restoring degraded lands. Annual Review of Environment and Resources *46*, 000-000 (in press).

195. Lewandowsky, S., Risbey, J.S., Smithson, M., Newell, B.R., and Hunter, J. (2014). Scientific uncertainty and climate change: Part I. Uncertainty and unabated emissions. Climatic Change *124*, 21–37.

196. Howe, L.C., Macinnis, B., Krosnick, J.A., Markowitz, E.M., and Socolow, R. (2019). acceptance of climate scientists ' predictions. Nature Climate Change *9*.

197. Luo, Y.Q., Randerson, J.T., Abramowitz, C., Bacour, e., Blyth, E., Carvalhais, N., Ciais, P., Dalmonech, D., Fisher, J.B., Fisher, R., et al. (2012). A framework of benchmarking land models. Biogeosciences *10*, 3857–3874.

198. Arneth, A., Niinemets, Ü., Pressley, S., Bàck, J., Hari, P., Karl, T., Noe, S., Prentice, I.C., Serça, D., Hickler, T., et al. (2007). Process-based estimates of terrestrial ecosystem isoprene emissions: Incorporating the effects of a direct CO2-isoprene interaction. Atmospheric Chemistry and Physics *7*, 31–53.

199. De Kauwe, M.G., Medlyn, B.E., Zaehle, S., Walker, A.P., Dietze, M.C., Hickler, T., Jain, A.K., Luo, Y., Parton, W.J., Prentice, I.C., et al. (2013). Forest water use and water use efficiency at elevated CO_2: a model-data intercomparison at two contrasting temperate forest FACE sites. Global Change Biology *19*, 1759–1779.

200. Hickler, T., Smith, B., Prentice, I.C., Mjöfors, K., Miller, P., Arneth, A., and Sykes, M.T. (2008). CO_2fertilization in temperate FACE experiments not representative of boreal and tropical forests. Global Change Biology *14*, 1531–1542.

201. Morales, P., Sykes, M.T., Prentice, I.C., Smith, P., Smith, B., Bugmann, H., Zierl, B., Friedlingstein, P., Viovy, N., Sabate, S., et al. (2005). Comparing and evaluating process-based ecosystem model predictions of carbon and water fluxes in major European forest biomes. Global Change Biology *11*, 2211–2233.

202. Olin, S., Schurgers, G., Lindeskog, M., Wårlind, D., Smith, B., Bodin, P., Holmér, J., and Arneth, A. (2015). Modelling the response of yields and tissue C : N to changes in atmospheric CO₂ and N management in the main wheat regions of western Europe. Biogeosciences *12*, 2489–2515.

203. Smith, B., Wårlind, D., Arneth, A., Hickler, T., Leadley, P., Siltberg, J., and Zaehle, S. (2014). Implications of incorporating N cycling and N limitations on primary production in an individual-based dynamic vegetation model. Biogeosciences *11*, 2027–2054.

204. Miloslavich, P., Bax, N.J., Simmons, S.E., Klein, E., Appeltans, W., Aburto-Oropeza, O., Andersen Garcia, M., Batten, S.D., Benedetti-Cecchi, L., Checkley, D.M., et al. (2018). Essential ocean variables for global sustained observations of biodiversity and ecosystem changes. Global Change Biology *24*, 2416–2433.

205. Lawrence, D.M., Hurtt, G.C., Arneth, A., Brovkin, V., Calvin, K. V, Jones, A.D., Jones, C.D., Lawrence, P.J., de Noblet-Ducoudre, N., Pongratz, J., et al. (2016). The Land Use Model Intercomparison Project (LUMIP) contribution to CMIP6: rationale and experimental design. Geoscientific Model Development *9*, 2973–2998.

206. Le Quéré, C., Andrew, R.M., Canadell, J.G., Sitch, S., Korsbakken, J.I., Peters, G.P., Manning, A.C., Boden, T.A., Tans, P.P., Houghton, R.A., et al. (2016). Global Carbon Budget 2016. Earth Syst Sci Data *8*, 605–649.

207. Rabin, S.S., Melton, J.R., Lasslop, G., Bachelet, D., Forrest, M., Hantson, S., Kaplan, J.O., Li, F., Mangeon, S., Ward, D.S., et al. (2017). The Fire Modeling Intercomparison Project (FireMIP), phase 1: experimental and analytical protocols with detailed model descriptions. Geoscientific Model Development *10*, 1175–1197.

208. Sitch, S., Friedlingstein, P., Gruber, N., Jones, S.D., Murray-Tortarolo, G., Ahlström, A., Doney, S.C., Graven, H., Heinze, C., Huntingford, C., et al. (2015). Recent trends and drivers of regional sources and sinks of carbon dioxide. Biogeosciences *12*, 653–679.

209. Lotze, H.K., Tittensor, D.P., Bryndum-Buchholz, A., Eddy, T.D., Cheung, W.W., Galbraith, E.D., Barange, M., Barrier, N., Bianchi, D., Blanchard, J.L., et al. (2018). Ensemble projections of global ocean animal biomass with climate change. bioRxiv, 467175.

210. Le Quéré, C., Andrew, R.M., Canadell, J.G., Sitch, S., Ivar Korsbakken, J., Peters, G.P., Manning, A.C., Boden, T.A., Tans, P.P., Houghton, R.A., et al. (2018). Global Carbon Budget 2018. Earth System Science Data.

Annex 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[83,197], 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[198–203]). Recent approaches allow scoring of model performance against a wide range of observations for global vegetation models[83]. 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. Specialised experiments or datasets, such as free-air carbon enrichment studies, herbivore exclosures or remotely-sensed trait information[84–86] 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 modelled processes[83]. 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 spatio-temporal scales, whereas biodiversity data are more disparate and contain many gaps (e.g. the GOOS marine initiative[204]), 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[138]. 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 modelling) and in coupled models (e.g., related to carbon cycle-climate feedbacks)[42,44,139–142]. 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 to the spread in output within a model ensemble.

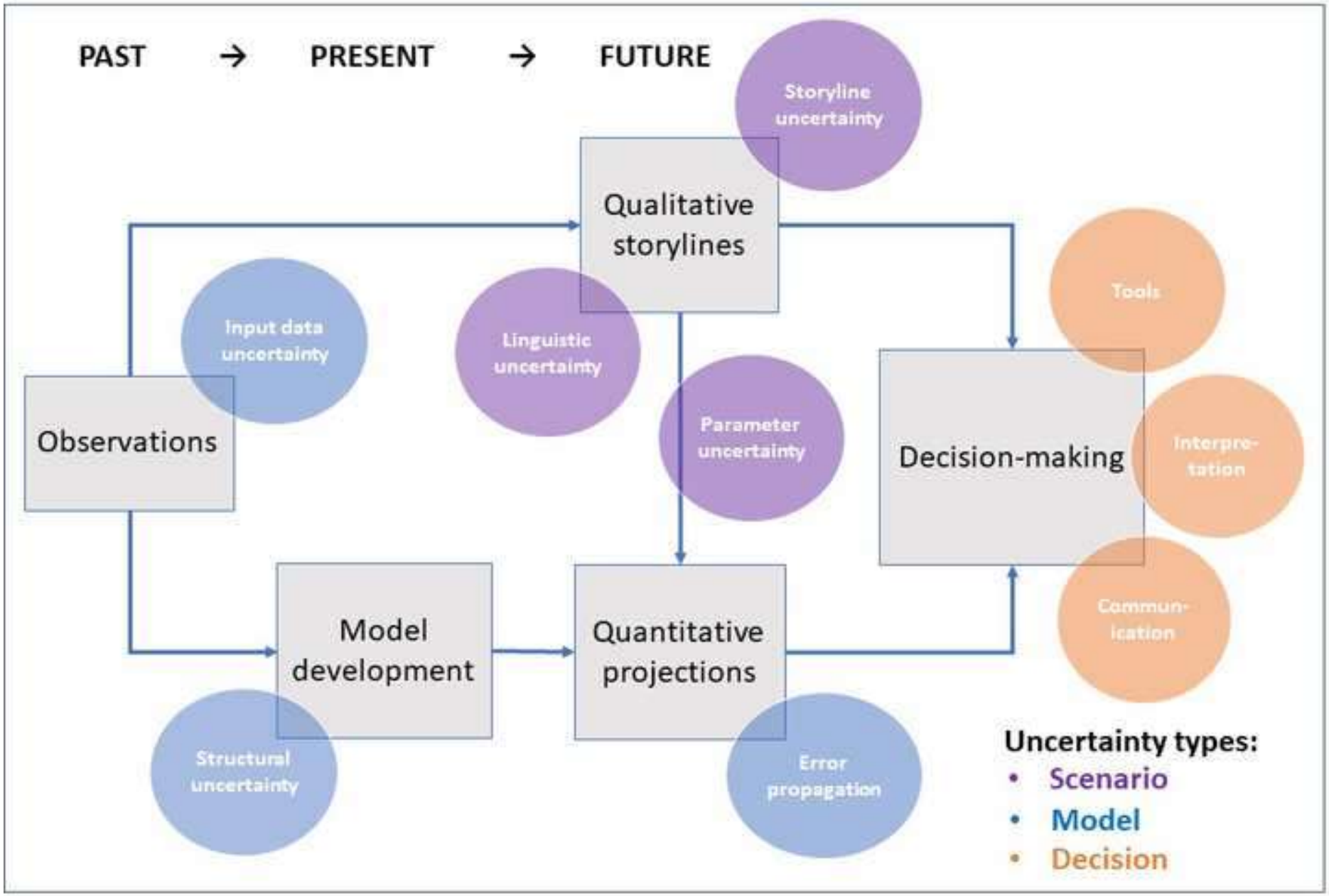
The currently most widely used approaches to quantify model uncertainty in climate change, land-use change, exploitation and ecosystem modelling are inter-comparisons and model-ensembles[7,205–208]. Ensemble modelling has proven highly beneficial for improving the credibility of climate change projections 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[9,209]).

In model inter-comparisons, different models that address a similar question are run using a standardised 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[15,94,138]. 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 fulfil 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[210]. In view of the often still untested model structural and parameter uncertainties, deriving probabilistic estimates of uncertainty from model ensembles must be viewed critically[138].

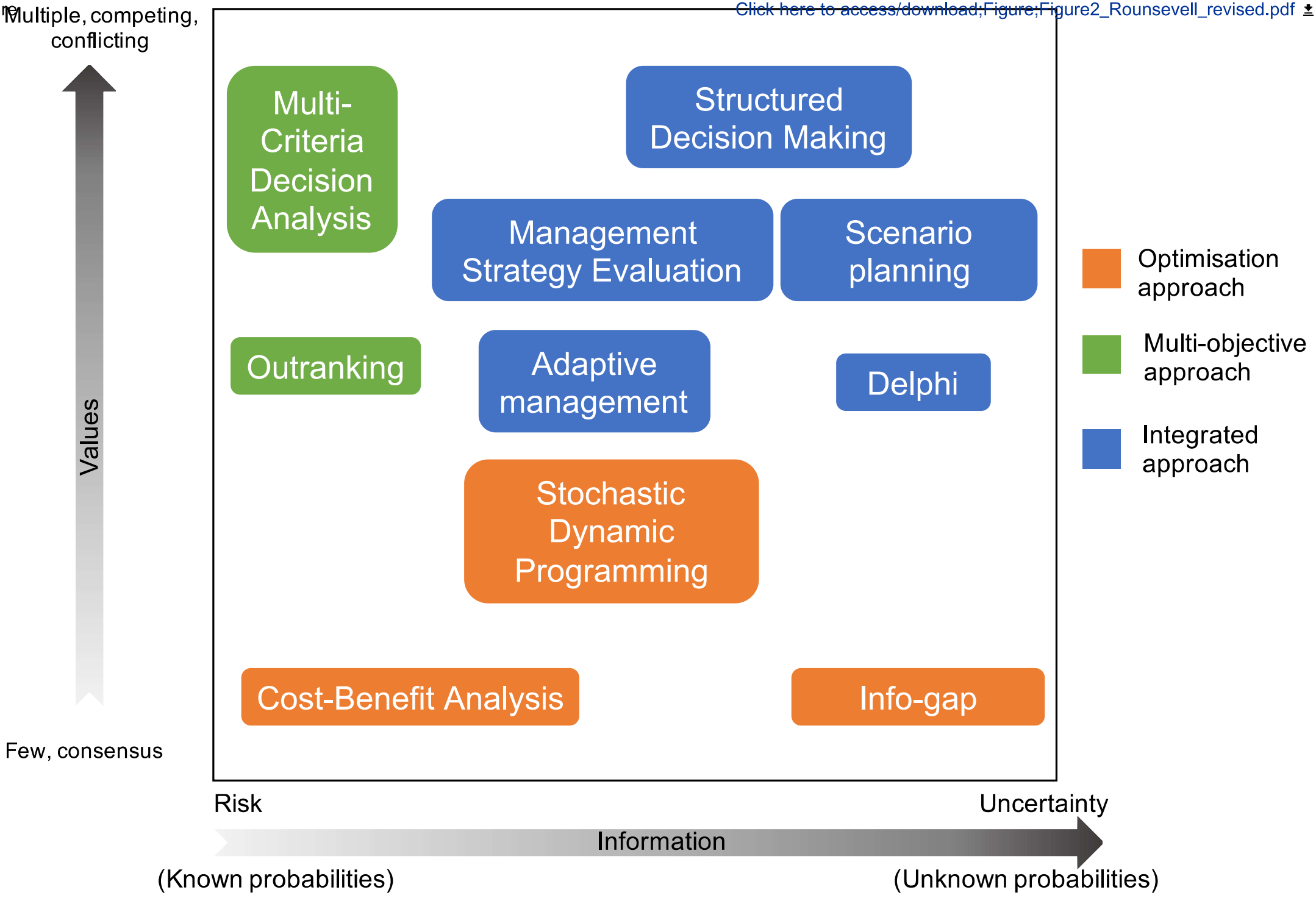
Figure

Click here to access/download;Figure;Figure1_Rounsevell.jpg



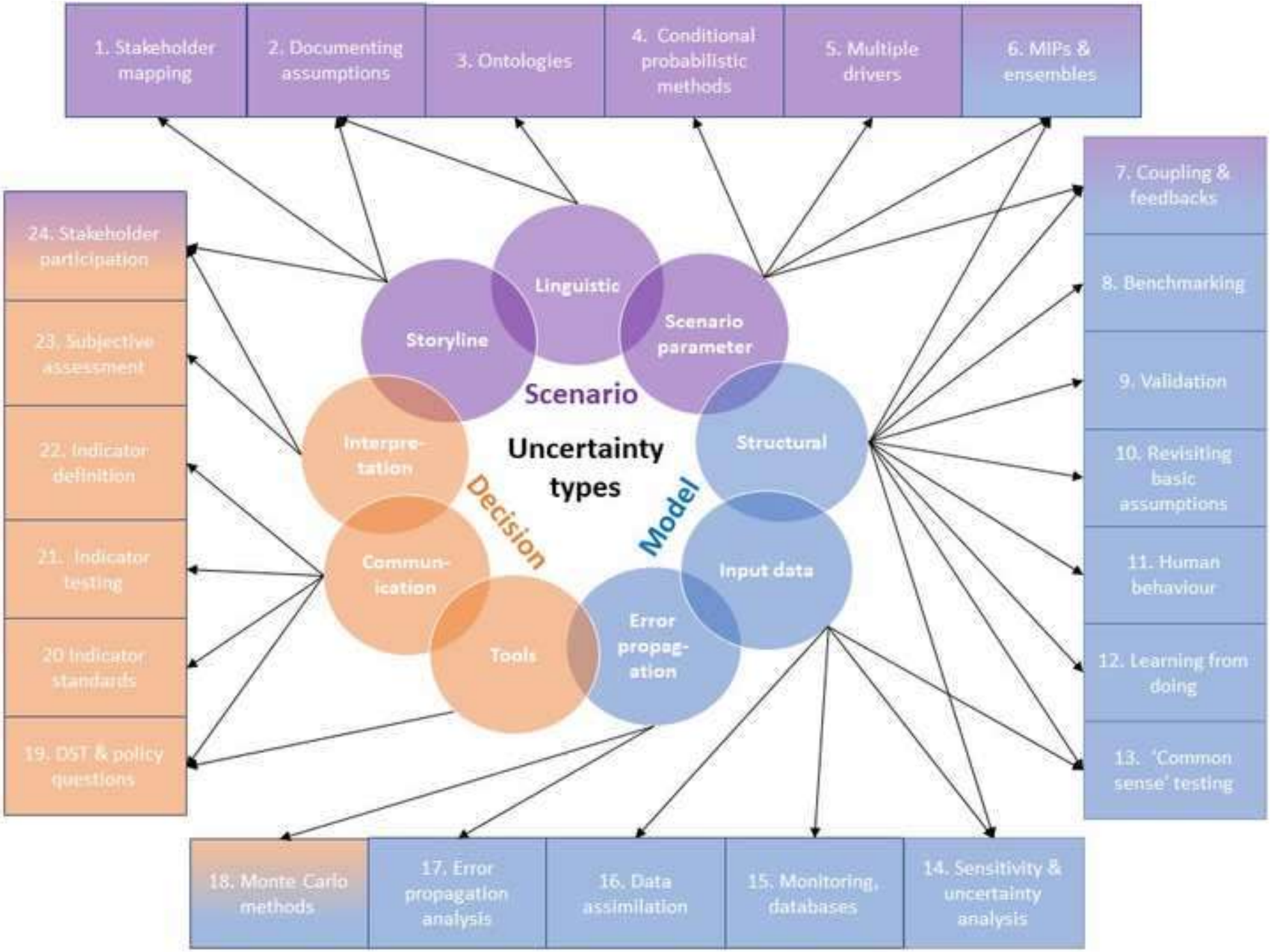
Figure

Click here to access/download;Figure;Figure2_Rounsevell_revised.pdf



Figure

Click here to access/download;Figure;Figure3_Rounsevell_revised.jpg





https://dspace.org/

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

Rounsevell, Mark D. A.; Arneth, Almut; Brown, Calum; Cheung, William W. L.; Gimenez, Olivier ...

2021-07-23
Elsevier
https://doi.org/10.1016/j.oneear.2021.06.003
Rounsevell MDA, Arneth A, Brown C, et al., (2021) Identifying uncertainties in scenarios and models of socio-ecological systems in support of decision-making. One Earth, Volume 4, Issue 7, July 2021, pp. 967-985

Downloaded from a DSpace repository. https://dspace.org/