

Exploratory modeling for analyzing coupled human-natural systems under uncertainty

Moallemi, Enayat A.; Kwakkel, Jan; de Haan, Fjalar J.; Bryan, Brett A.

DOI

[10.1016/j.gloenvcha.2020.102186](https://doi.org/10.1016/j.gloenvcha.2020.102186)

Publication date

2020

Document Version

Accepted author manuscript

Published in

Global Environmental Change

Citation (APA)

Moallemi, E. A., Kwakkel, J., de Haan, F. J., & Bryan, B. A. (2020). Exploratory modeling for analyzing coupled human-natural systems under uncertainty. *Global Environmental Change*, 65, Article 102186. <https://doi.org/10.1016/j.gloenvcha.2020.102186>

Important note

To cite this publication, please use the final published version (if applicable). Please check the document version above.

Copyright

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights. We will remove access to the work immediately and investigate your claim.

Exploratory modeling for analyzing coupled human-natural systems under uncertainty

Enayat A. Moallemi^{1,2}, Jan Kwakkel³, Fjalar J. de Haan¹, Brett A. Bryan¹

¹ Centre for Integrative Ecology, School of Life and Environmental Sciences, Deakin University, Melbourne, Australia.

² Designing Systems for Informed Resilience Engineering (DeSIRE), The 4TU Centre for Resilience Engineering (4TU.RE), The Netherlands.

³ Faculty of Technology, Policy and Management, Delft University of Technology, The Netherlands.

Corresponding author: Enayat A. Moallemi, e.moallemi@deakin.edu.au

Abstract

Modeling is a crucial approach for understanding the past and exploring the future of coupled human-natural systems. However, uncertainty in various forms challenges inferences from modeling results. Model-based support for decision-making has increasingly adopted an emerging *exploratory* approach. This approach addresses uncertainty explicitly through systematically exploring the implications of modeling assumptions, aiming to enhance the *robustness* of inferences from models. Despite a variety of applications, the extent and the way(s) that exploratory modeling can deal with the challenges that arise from the uncertainty and complexity of decision-making with stakeholders has not yet been systematically framed. We address this gap in two ways. First, we present a taxonomy of the ways that exploratory modeling can be used to inform robust inferences in coupled human-natural systems by mapping the technical capabilities of this approach in relation to the diversity of past applications. This subsequently guides an investigation of the practical benefits and challenges of these capabilities in handling uncertainty and complexity. Second, we discuss different ways for integrating genuine stakeholder engagement into exploratory modeling through transdisciplinary research. Finally we outline some priorities for future expansion of this research area.

Keywords: Decision-making, adaptation, uncertainty, robustness, stakeholder, participatory, sustainability.

1 Introduction

Significant concerns have arisen from impacts of global change on water resources, ecosystems, land use, and food production, worldwide (Eker *et al.*, 2019; Gao & Bryan, 2017; Khazaei *et al.*, 2019; Quinn *et al.*, 2018). Data on the not-yet-experienced states and multi-decadal impacts of global change are limited given the presence of many highly interrelated, complex, variable, and poorly understood human-natural systems and because of the long

timescales involved (Funtowicz & Ravetz, 1990; Lamontagne *et al.*, 2019; Oddo *et al.*, 2017; Weaver *et al.*, 2013). Despite the complexity and limited data availability, computer modeling and simulation are widely-used tools to understand environmental and societal risks of global change on human-natural systems (Bilskie *et al.*, 2016; Fischer *et al.*, 2005). For the purpose of this article, we define a *model* as a formal description of human knowledge about the nexus of systems driven by physical, chemical, and biological mechanisms as well as societal, economic, and political forces. A *simulation* means using such a model, running it to inspect how these systems manifest and interact, usually as a function of time. A diverse set of models and model-based inferences is used to underpin decision-making under global change spanning areas such as food and diet (Bijl *et al.*, 2017; Eker *et al.*, 2019; Malek *et al.*, 2020), climate adaptation (JGCRI, 2017; Mayer *et al.*, 2017; Small & Xian, 2018), and land use (Doelman *et al.*, 2018; Gao & Bryan, 2017). Models can play an important role in our understanding of the Earth's climate, water, land dynamics, and energy conditions in the past (e.g., cycles of ice ages over the past two million years) and the ways that this can change in the future (e.g., via global warming). These modeling efforts have underlined the importance of systematically dealing with complexity and uncertainty as defining properties of all human-natural systems (Verburg *et al.*, 2016) and of the policy design process (Mercure *et al.*, 2016). Here we analyze the extent of modeling capabilities, challenges, and opportunities for navigating the complexity and uncertainty that arise in understanding and managing coupled human-natural systems.

The knowledge we put into models is, in most cases (except perhaps *purely* mathematical or logical models), imperfect and uncertain. Uncertainties lurk throughout different facets of modeling and simulation including conceptual framing, boundary conditions, the choice of modeling paradigms, model structures and schematizations, input data, scenario assumptions, and performance metrics, as systematically pointed out by Morgan *et al.* (1990), Walker *et al.* (2003), Lempert *et al.* (2003), McPhail *et al.* (2018), and Khatami *et al.* (2019). Traditionally, a consolidative approach to modeling — as Bankes (1993) stated — incorporates all known facts into a best estimate package which can then be used for predicting system behavior (Lempert & Collins, 2007). Such a consolidative approach frames uncertainty as something that is imaginable. However, future climate and environmental conditions and their societal risks are a not-yet-experienced state of human-natural systems. Therefore, *a priori* calibration of models will not produce reliable long-term forecasts (Weaver *et al.*, 2013). Modeling approaches that rely on things being imaginable — if perhaps improbable and implausible — cannot usually deal with so-called ‘Grey Swans’ or ‘unknown knowns’, that is unexpected consequences of that which we already knew (Di Baldassarre *et al.*, 2016). Consolidative approaches also fail when confronted with missing data or inadequate theories (Weaver *et al.*, 2013). Unknown knowns, missing data, and inadequate theories are not amenable to probabilistic characterization and may not even be assigned a likelihood of occurrence (Maier *et al.*, 2016). Their values are either unknowable at present, or no agreement can be reached about their values because of the presence of multiple stakeholders with different, often contrasting views. This range of uncertainties which cannot be meaningfully couched as probabilities, initially discussed in the context of Knightian uncertainty (Knight, 1921), has been recently termed *deep uncertainty* (Lempert *et al.*, 2003) or *severe uncertainty* (Ben-Haim, 2006).

Exploratory modeling is an approach, a philosophy, of modeling which is concerned specifically with dealing with deep uncertainty and complexity (Bankes, 2002b; Lempert *et al.*, 2003). The approach was conceived and pioneered at the RAND Corporation, notably by Hodges (1991), Hodges and Dewar (1992), Bankes (1993), Bankes (2002b), Lempert (2002), Lempert *et*

al. (2003), and Bankes *et al.* (2013). The central idea of exploratory modeling is to let go of the ideal of a model as a predictive tool which turns best available knowledge into a best estimate, and to abandon the notion of a good model being one that gives an accurate prediction of the most likely development of the system (Kwakkel & Haasnoot, 2019). Rather, a model is seen as a thinking aid where the aim is to capture relevant uncertainties by enumerating a range of possible assumptions and systematically exploring the implications of these assumptions via large numbers of computational experiments.

The core idea of exploratory modeling has been adopted in theory and model development aimed at explaining a potential phenomenon of interest or to test and refine a set of hypotheses and assumptions (de Haan *et al.*, 2016). This corresponds to Bankes (1993) *data-driven* and *model-driven* exploratory modeling. The former aims to reveal regularities, patterns, goodness-of-fit, and structure of a dataset, while the latter asks whether and under what conditions several models of the same phenomenon can produce similar behavior (Auping *et al.*, 2016). Exploratory modeling has been adopted much more widely in model-based decision support for a variety of human-natural systems under deep uncertainty (Helgeson, 2020), for example in water resource management (Gold *et al.*, 2019; Trindade *et al.*, 2017; Trindade *et al.*, 2019) and in supporting climate-related decisions (Isley *et al.*, 2015; Lamontagne *et al.*, 2019; Sriver *et al.*, 2018; Weaver *et al.*, 2013). Exploratory modeling is also a key model-based approach for supporting the design of adaptive policy pathways that aim to combine low-regret, short-term actions with long-term solutions to adapt (if needed) to uncertain future change (Haasnoot *et al.*, 2013; Trindade *et al.*, 2019; Wise *et al.*, 2014). This approach enables the investigation of the efficacy of monitoring systems for adapting to global change (Haasnoot *et al.*, 2018; Raso *et al.*, 2019). These widely-used applications of exploratory modeling are *question-driven* and case-based (Boero & Squazzoni, 2005), designed to illuminate robust policy choices and develop adaptation plans for a specific decision problem.

Several studies have attempted to inform exploratory modeling through detailed classifications of decision support frameworks (Herman *et al.*, 2020; Herman *et al.*, 2015; Kwakkel & Haasnoot, 2019; Moallemi *et al.*, 2020b), scenario approaches (Guivarch *et al.*, 2017; Trutnevyte *et al.*, 2016), robustness metrics (McPhail *et al.*, 2018), and scenario selection (McPhail *et al.*, 2020). However, these have either been sector-specific (e.g., water), method-specific, or focused on a particular topic (e.g., scenarios) rather than discussing the bigger picture and the synthesis of different topics. This has led to a major gap where exploratory modeling, as an emerging field with interlinkages between its different areas, has not yet been systematically framed to guide a broader audience in extending and combining its capabilities in new sectoral domains (e.g., integrated assessment modeling (Obersteiner *et al.*, 2016)). This situation has an analogy with the related area of sensitivity analysis where there are similar concerns around being mostly method- or domain-focused (Saltelli *et al.*, 2019).

Here we formulate a taxonomy of exploratory modeling approaches for decision-making to map emerging technical capabilities in addressing uncertainty and complexity (Section 2). While past studies have discussed specific details of these capabilities, we focus on the combination of these capabilities and how they can be used to deal with the challenges and opportunities that arise in the modeling of coupled human-natural systems. We analyze several recent studies through the lens of this taxonomy to illustrate the diversity of the field (Section 3). We discuss the strengths of the iterative process of exploratory modeling from which researchers can benefit and reflect on some of the known issues and challenges that remain to be addressed

(Section 4). As a direction for future research, we discuss different ways for engaging with stakeholders in exploratory modeling for the co-creation of model inferences as an emerging and popular topic in the literature and a major gap in the literature (Section 5). Our motivation is to encourage and guide researchers and practitioners across disciplines to adopt exploratory modeling beyond the currently established decision-making frameworks and in new applications for sustainability. A simple and widely accessible description of exploratory modeling can pave the way for its further contribution to decision-making under uncertainty in high-impact international science-policy arenas such as the Sustainable Development Goals (UN, 2015), the Intergovernmental Panel on Climate Change (IPCC, 2019), and the Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES, 2019).

2 A taxonomy of exploratory modeling for decision support

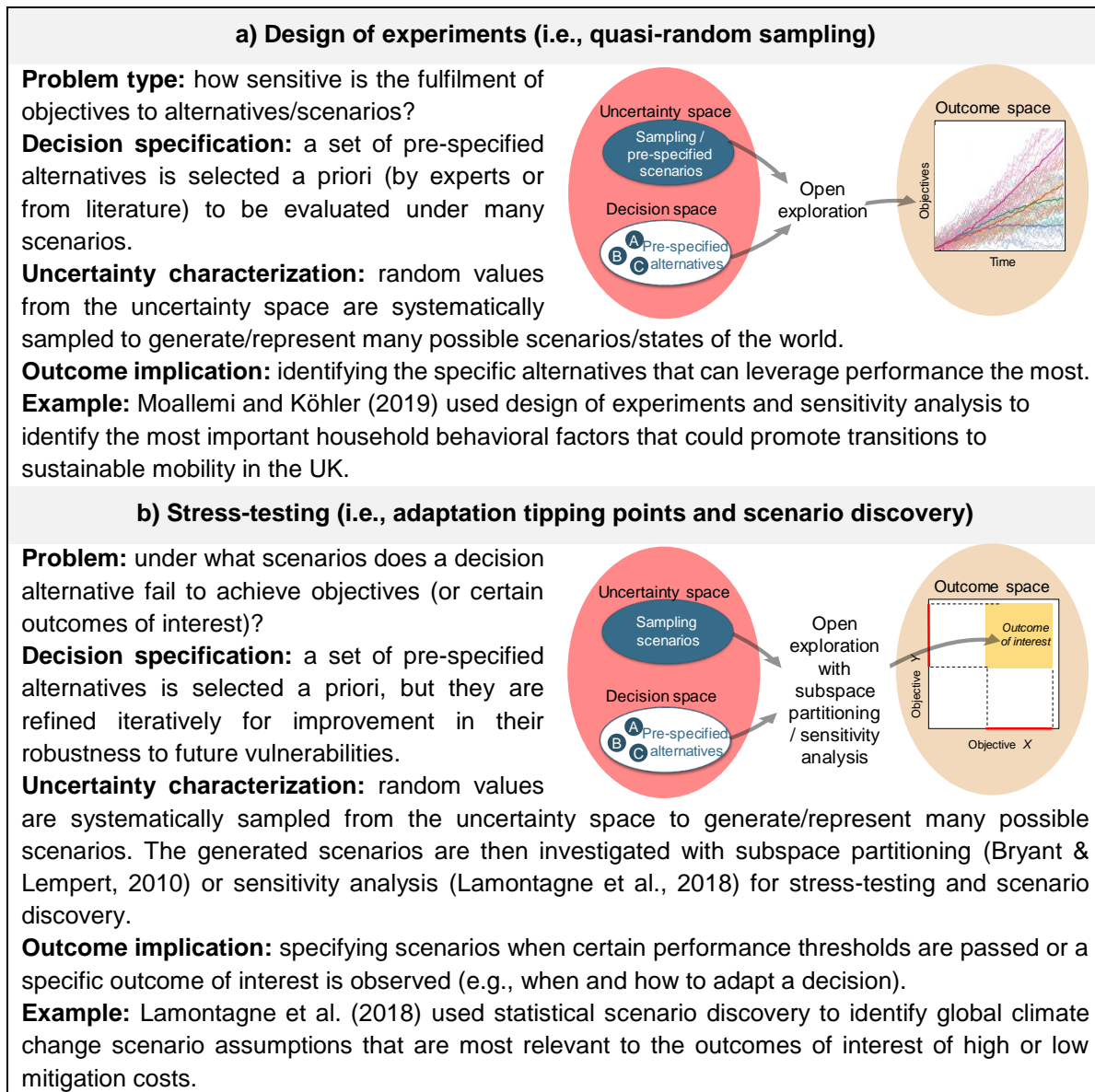
The use of exploratory modeling in supporting decision-making often starts by formulating an initial decision problem that can be revised iteratively throughout the modeling process (Quinn *et al.*, 2017). Typically, the problem formulation involves the specification of scenarios, decision alternatives, robustness metrics, and models (Lempert *et al.*, 2003; Walker, 2000). A scenario, in the context of exploratory modeling, is a fully specified realization of sampled values from the model parameter uncertainty space, representing a future state of the world. An example from climate change scenarios is a multi-dimensional uncertainty space created by the combination of different growth rates for population and the economy and different time series for the price of fossil fuels and renewable energy technology in the future where each point sampled from this space is a single socio-economic scenario (Riahi *et al.*, 2017). A decision alternative is a vector of decision variables/levers in a multi-dimensional decision space that fully specifies all required candidate actions/choices. An example of a lever is a feed-in tariff or renewable energy credit price in the electricity sector, where a vector from a specific value of each lever forms a decision alternative for supporting the renewable energy generation. Models are used to generate computational experiments, analyzing the implications of decision alternatives over the diversity of scenarios in an outcome space. The outcome space contains the (potential) results of the computational experiments (i.e., simulation runs) which could be post-processed using various robustness metrics, indicating how well the system performs under a range of plausible conditions (e.g., absolute performance or regret) (McPhail *et al.*, 2018).

Different exploratory modeling approaches share the core idea of systematically analyzing the implications of decision and uncertainty spaces in the outcome space. However, they can be implemented in different ways through open exploration or directed search. Under uncertainty, there is a large set of possible assumptions from which we need to draw inferences (i.e., decision insights/conclusions that we obtain from results). Open exploration through the *design of experiments* and *stress-testing* is one way of investigating global properties of the assumption set. These approaches involve systematic sampling (e.g., via Latin Hypercube or Monte Carlo Sampling) from the uncertainty/decision space to generate a series of computational experiments with good space filling properties. The experiments are used to run the model and to analyze the model results for policy-relevant inferences. Open exploration generates a broad understanding of the implications and vulnerabilities of alternative assumptions. However, the weakness of open exploration emerges for systems with complex combinations of decisions that require the attainment of high levels of sustained performance often for conflicting objectives. Several studies have shown that in many systems without more formalized directed search, an

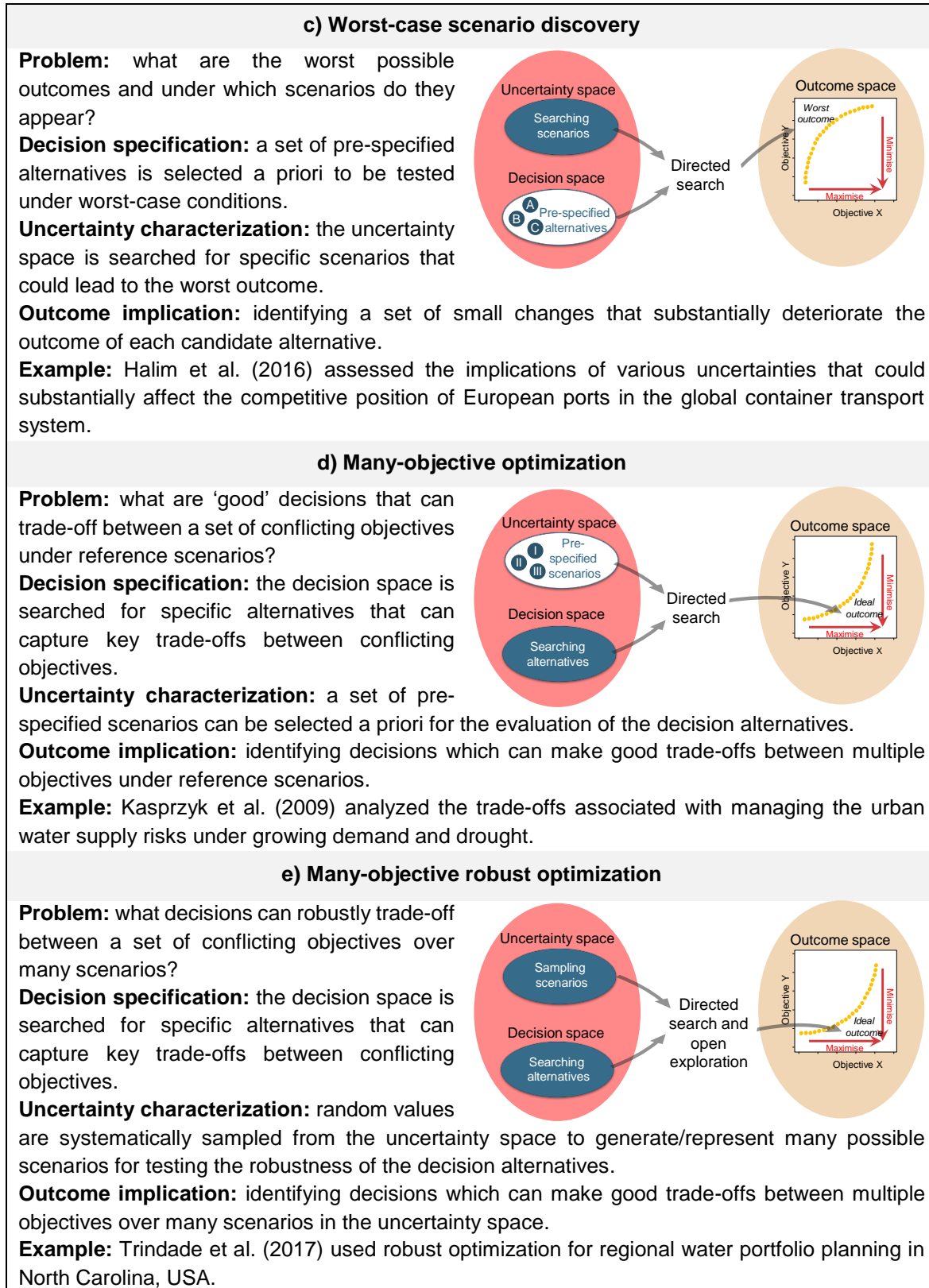
open exploration is myopic in focusing on a limited set of alternatives and in not capturing key trade-offs (Gold *et al.*, 2019; Zeff *et al.*, 2014). This initially led to early work (Kasprzyk *et al.*, 2009; Reed *et al.*, 2008) on the use of (*many-objective*) *optimization* algorithms (Halim *et al.*, 2016; Kollat & Reed, 2006; Reed *et al.*, 2013) to search for specific decisions and scenarios which lead to properties of interest in the outcome space. In other words, optimization investigates closely the reasons (assumptions) behind the properties of interest and finds specific inferences. More recent work has shown that including open exploration and deep uncertainties in directed search can yield substantially more robust and effective candidate decisions, which has led to the increasing use of *many-objective robust optimization* (Bartholomew & Kwakkel, 2020; Eker & Kwakkel, 2018; Quinn *et al.*, 2018; Trindade *et al.*, 2019).

Box 1 and Box 2 present the taxonomy of these exploratory modeling approaches, articulating the "what" and "why" of different components of the problem framing and characterizing the *problem type* (i.e., the type of research problem that can be answered), *decision specification* (i.e., how decision alternatives are generated), *uncertainty characterization* (i.e., how scenarios are generated), type of *outcome implication* (i.e., the inferences obtained from the analysis), and an *example* of an application. We also further elaborated three examples from different sectors to show how these approaches lead to different types of robust inferences in Appendix C. While we characterize different exploratory modeling approaches, we avoid rigid divisions (i.e., dichotomy or polychotomy) between them as they can overlap and interact with one another. For example, in Box 1, design of experiments and stress-testing are not mutually exclusive, and they can both use sensitivity analysis. Stress-testing can be implemented using sensitivity analysis to identify those factors that most influence certain properties of interest (Lamontagne *et al.*, 2018). However, stress-testing can be implemented in other ways too, for example using the patient rule-induction method (Guivarch *et al.*, 2016), classification and regression trees (CART) (Lempert *et al.*, 2008), many-objective optimization (Kwakkel, 2019), and logistic regression (Quinn, 2017). Conversely, not all sensitivity analysis processes in exploratory modeling are for the purpose of stress-testing. Sensitivity analysis can also be used in the design of experiments for investigating how variation in model output can be attributed to variations in inputs to identify the most important decision alternatives or scenarios. See Appendix B for a further discussion about sensitivity analysis in relation to exploratory modeling.

Box 1. Exploratory modeling approaches. (a) design of experiments, (b) stress-testing.



Box 2. Exploratory modeling approaches (cont'd). (c) worst-case scenario discovery, (d) many-objective optimization, and (e) many-objective robust optimization.



How do these different exploratory modeling approaches fit together? There has been a growing interest in combining exploratory modeling approaches to better address complex policy questions. For example, Watson and Kasprzyk (2017) used the strength of scenario discovery in vulnerability assessment to complement the analysis of candidate decisions identified through many-objective optimization. This combination of exploratory modeling approaches has led to new ways to support decision-making, broadly categorized into two (not mutually exclusive) groups (Herman *et al.*, 2020; Kwakkel & Haasnoot, 2019): *robustness frameworks* that often focus on static plans and suggest decisions which work under a range of uncertain futures, and; *adaptation frameworks* that focus on the importance of flexibility in decision-making and suggest adaptive decisions that can respond to emerging challenges and opportunities over time (Figure 1).

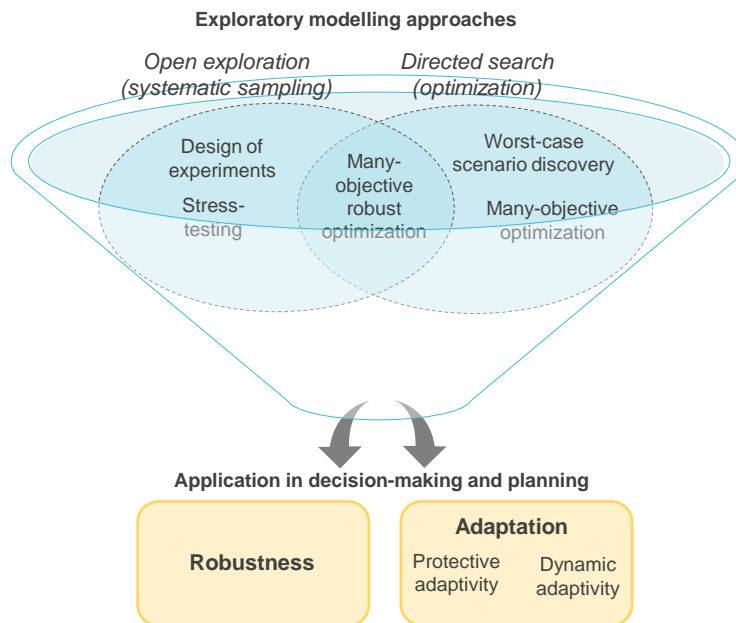


Figure 1. An overview of potential approaches of exploratory modeling and their applications in decision-making and planning. Different types of exploratory modeling approaches can be combined with one another in support of robust or adaptive decision-making.

Examples of robustness frameworks include Robust Decision Making (Lempert *et al.*, 2003), Info-Gap (Ben-Haim, 2019) and Decision Scaling (Brown *et al.*, 2012). They often use stress-testing (Lempert *et al.*, 2013) or worst-case scenario discovery (Halim *et al.*, 2016) to identify system vulnerabilities under deep uncertainty and then use the design of experiments (Moallemi *et al.*, 2017) or many-objective (robust) optimization (Trindade *et al.*, 2017) to recommend decisions with robust performance over scenarios. The process of designing a plan with robustness frameworks is often less dependent on uncertainty characterization due to the presence of the uniformly sampled values from the uncertainty space and the assessment of decision alternatives over the ensemble of sampled scenarios. Adaptation frameworks recommend decision alternatives that can be adapted over time in response to a clear signal that they are necessary from new information collected. Some adaptation frameworks propose a basic plan with protective contingency measures to be implemented if needed (protective adaptivity),

for example in Assumption-based planning (Dewar *et al.*, 1993) and Dynamic Adaptive Planning (Kwakkel *et al.*, 2010). Others propose a series of decisions with possible transfers between them that should be implemented depending on how the future unfolds (i.e., dynamic adaptivity), for example in Dynamic Adaptive Policy Pathways (Haasnoot *et al.*, 2013). In both cases, stress-testing and worst-case scenario discovery are often used to identify when the contingency measures for a basic plan may be needed or when a decision fails to meet the objectives and a different decision is required. Design of experiments and many objective (robust) optimization can also be used in optimizing the sequence, timing, and threshold values of a variable to adapt a decision through triggering a contingency measure or transferring to a new decision (Fletcher *et al.*, 2019; Kwakkel *et al.*, 2015). The decision-making process in adaptation frameworks is generally more dependent on uncertainty specification as it requires specifying the uncertainty range as well as the sequences of decision alternatives over time (Herman *et al.*, 2020).

3 Applying the taxonomy

In this section we demonstrate the diverse applications of exploratory modeling as a field according to the proposed taxonomy and provide specific examples analyzing coupled human-natural systems under uncertainty using various exploratory modeling approaches. We summarized selected studies that have used exploratory modeling (Table 1), organized under the framing of the taxonomy (Boxes 1 and 2), their context (i.e., water, climate, energy and transport, infrastructure, and land use and food), and type of case study (i.e., illustrative/hypothetical or real-world). The list of selected studies in Table 1 is not meant to be exhaustive nor represent the entire literature on exploratory modeling, but rather illustrates the use of our taxonomy and the diversity of the field across different contexts (see Appendix C for the rationale behind selecting these papers). We refer readers interested in a systematic review to recent reviews on scenario analysis (Guivarch *et al.*, 2017), decision-making/planning (Herman *et al.*, 2020; Kwakkel & Haasnoot, 2019), sensitivity and uncertainty analysis (Maier *et al.*, 2016; Pianosi *et al.*, 2016), and many-objective optimization algorithms (Maier *et al.*, 2019; Reed *et al.*, 2013), where exploratory modeling is used as model-based support. We also provide a detailed description of three exploratory modeling studies (Appendix C) from water, infrastructure, and energy contexts to further familiarize modelers with the implementation process and the type of results and insights obtained.

Table 1. Examples of recent studies focused on exploratory modeling of different types, contexts, and applications. The examples are selected and categorized in the table based on the authors' knowledge of studies and they do not represent a comprehensive overview of the literature (see Appendix C for the selection process).

Examples	Stress-testing	Design of experiments	Worst-case scenario discovery	Many-objective optimization	Many-objective robust optimization	Water	Climate	Energy & mobility	Infrastructure	Land use (also food)	Illustrative	Case study
Giudici et al. (2020)	●											
Lamontagne et al. (2019)	●	●			●		●					●
Hall et al. (2019)	●	●					●		●			●
Gold et al. (2019)	●				●	●			●			●
Moallemi and Köhler (2019)		●						●				●
Groves et al. (2019)	●					●	●					●
Eker et al. (2019)	●	●								●		●
Babovic and Mijic (2019)	●						●		●			●
Sriver et al. (2018)	●	●					●		●			●
Lamontagne et al. (2018)	●	●					●				●	
Eker and Kwakkel (2018)	●				●	●					●	
Marcos-Martinez et al. (2018)		●					●			●		●
Quinn et al. (2018)	●				●	●	●					●
Kwakkel (2017)	●	●	●	●	●	●	●				●	
Gao and Bryan (2017)		●				●	●	●		●		●
Watson and Kasprzyk (2017)	●				●	●						●
Quinn et al. (2017)			●		●	●	●		●			●
Trindade et al. (2017)	●				●	●			●			●
Moallemi et al. (2017)	●	●						●				●
Berntsen and Trutnevte (2017)	●							●				●
Bryan et al. (2016)		●					●			●		●
Zeff et al. (2016)	●				●	●	●		●			●
Herman et al. (2016)	●				●	●	●		●			●
Gao et al. (2016)		●					●			●		●
Carlsen et al. (2016)	●				●	●	●		●			●
Guivarch et al. (2016)	●						●				●	
Grundy et al. (2016)		●					●			●		●
Eker and van Daalen (2015)	●				●			●				●
Kwakkel et al. (2015)	●				●	●	●		●		●	●
Halim et al. (2016)	●		●				●		●			●
Borgomeo et al. (2014)	●	●				●	●		●			●
Herman et al. (2014)	●				●	●	●		●			●
Zeff et al. (2014)					●	●	●		●			●
Castelletti et al. (2014)					●	●	●		●			●
Zhao et al. (2014)		●								●		●
Giuliani et al. (2014)					●	●			●			●
Rozenberg et al. (2014)	●						●				●	
Hamarat et al. (2014)					●			●				●
Whateley et al. (2014)	●					●	●					●
Hamarat et al. (2013)	●				●			●			●	
Kasprzyk et al. (2013)	●				●	●	●		●			●
Song et al. (2013)		●								●		●
Lempert et al. (2013)	●	●					●		●			●
Nazemi et al. (2013)	●					●	●					●
Song et al. (2012)		●								●		●
Lempert and Groves (2010)	●	●				●	●		●			●
Bryant and Lempert (2010)	●	●						●			●	
Kasprzyk et al. (2009)				●		●	●		●			●
Kollat and Reed (2006)				●		●					●	

The trend of the selected studies in Table 1 shows that the treatment of uncertainty improved over time by re-appropriating established approaches such as sensitivity analysis and many-objective optimization for exploratory purposes under deep uncertainty, for example, through stress-testing and many-objective robust decision-making (Hall *et al.*, 2019; Lamontagne *et al.*, 2018; Watson & Kasprzyk, 2017). There is also a growing interest in capitalizing on the strengths of one approach to compensate for the limitations of others and the integrated use of different types of exploratory modeling (Moallemi *et al.*, 2018), for example, through combining stress-testing and robust optimization in decision-making frameworks (Eker & Kwakkel, 2018; Gold *et al.*, 2019; Trindade *et al.*, 2017). The abundance of various applications on real-world problems in Table 1 supports the practicality of exploratory modeling approaches and encourages their further use for decision-making across other applications and for new modeling purposes. While the contexts in which exploratory modeling has been applied are diverse, so far not all types of exploratory modeling have been widely used across different sustainability areas. There is, therefore, an opportunity for enhancing modeling under uncertainty in new contexts such as food and land systems, biodiversity, health, and ecology, beyond the standard use of scenario analysis and sensitivity analysis. Eker *et al.* (2019) provides a recent example of an exploratory modeling application in these emerging contexts where they used scenario discovery to identify a set of behavioral factors that can shift the global food system towards a more sustainable diet.

4 Benefits and challenges of exploratory modeling in practice

We investigate the motivations and the potential benefits of using exploratory modeling in support of good modeling practice and robust decision-making. We enumerate the benefits to argue for the further adoption of exploratory modeling addressing sustainability contexts more widely across coupled human-natural systems. We also discuss current limitations and potential challenges that modelers may face in the use of exploratory modeling. Reflection on current issues can highlight the areas for further improvement and direct future research in the field.

We frame the discussion of potential benefits and challenges in the context of the iterative process of model-based decision-making to clarify the impacts (Figure 2). According to Sterman (2000), model-based policy analysis typically starts by *problem articulation* for identifying the decision problem, requirements, and the current situation. It continues by *system conceptualization* for developing a conceptual model that can represent the problem at hand. The conceptual model, supported by data, is used in *model formulation* for setting up a simulation model. The formulated model, after *testing and validation* under uncertainty, works as a simulation engine in exploratory modeling to generate the system response under different assumptions. The validated model is used for the *policy evaluation* of decisions and scenarios to obtain robust inferences.

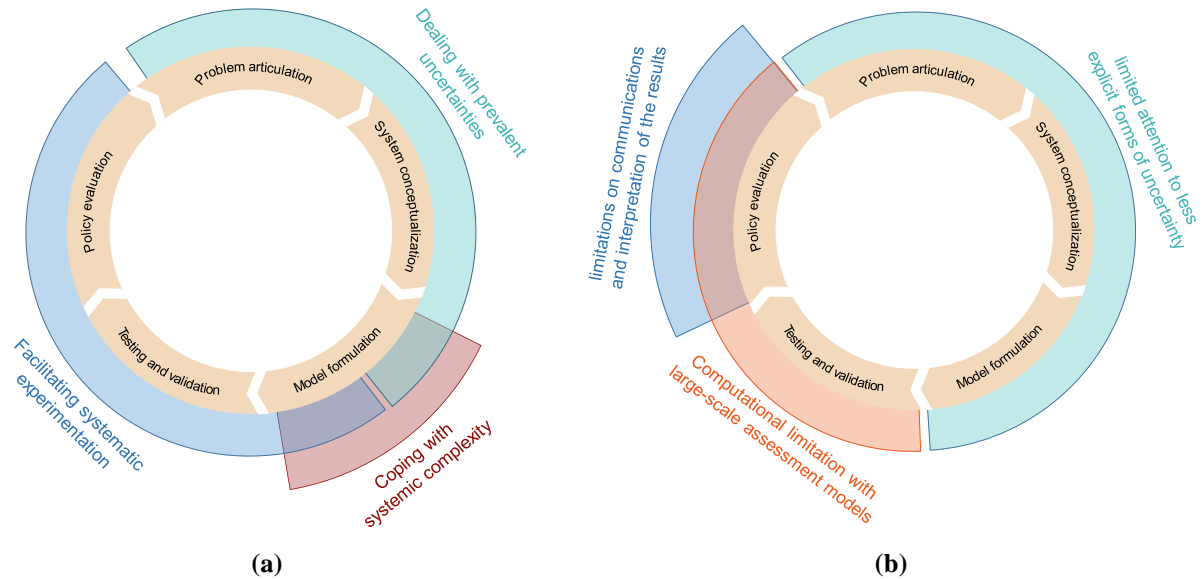


Figure 2. An overview of the benefits and challenges of exploratory modeling. (a) shows benefits and (b) shows challenges. The circular arrows represent the iterative steps in the general modeling process. The rings around the arrows show where potential benefits/challenges overlap with the modeling step(s).

4.1 Handling uncertainty

Coupled human-natural systems work in a context of multiple interacting climatic, technological, socio-economic, and political uncertainties (Quinn, 2017). Exploratory modeling has a major advantage in ‘*dealing with the prevalent uncertainties*’ of these systems, through evaluating models as hypotheses (Khatami *et al.*, 2020) and by a systematic exploration of the diversity of (model and dataset) assumptions with minimum prior judgements about their ranking or probability. This variety of assumptions can be reflected in different parts of the modeling process. Uncertainty can occur in framing a problem (problem articulation) (Quinn *et al.*, 2017), the implications of different datasets and system conceptualizations (in system conceptualization) (de Haan *et al.*, 2016; Moallemi *et al.*, 2017), and in the multiple alternative models of the same problem (in model formulation) (Auping *et al.*, 2016; Pruyt & Kwakkel, 2014).

Given these uncertainties, an exploratory approach helps modelers to investigate a wide range of assumptions which otherwise might have remained uninvestigated. A key advance of exploratory modeling in decision-making over conventional predict-then-act approaches is in where and how uncertainty is treated. Conventional approaches to decision-making address uncertainty *a priori* when decision-maker preferences and knowledge are elicited and imposed before performing any analysis (Tsoukiàs, 2008). In contrast, the adoption of exploratory modeling is more consistent with *a posteriori* analysis that opens up the space of alternative assumptions that can be made, in pursuit of increasing the robustness of inferences across a large range of possible uncertainties (Dessai & Hulme, 2007; Huskova *et al.*, 2016). In other words, robust inferences are obtained after a thorough exploration and a diverse search over rival framings of a problem, conflicting objectives, and divergent stakeholder preferences (Hadjimichael *et al.*, 2020b; Herman *et al.*, 2015). Shortridge and Zaitchik (2018) and Taner *et al.* (2019) are two recent examples of *a posteriori* analysis of likelihood after stress testing. Conventional approaches also rely on the maximization of expected utility and an optimal

performance as the criterion for a ‘good’ decision against a predicted future with the best-estimate probability distributions (Lempert, 2019). Instead, exploratory modeling uses robustness and flexibility as the mark of quality — that is whether a set of decisions performs well across many possible futures (Herman *et al.*, 2015; Herman *et al.*, 2014; Maier *et al.*, 2016; McPhail *et al.*, 2018), and whether decision performance remains insensitive to (or minimizes regret) and flexible in response to unforeseen futures (Weaver *et al.*, 2013).

Despite the potential to incorporate various forms of uncertainties, previous exploratory modeling studies usually only considered uncertainties in input parameters. This has led to the current gap in the literature, that is a ‘*limited attention to less explicit forms of uncertainty*’, which are often non-parametric. Such uncertainties can be reflected in different ways of valuing outcomes (in problem articulation) (Giuliani & Castelletti, 2016; McPhail *et al.*, 2018), variation in model structural relationships and equations (in model formulation) (Auping *et al.*, 2016; Moallemi *et al.*, 2017; Pruyt & Kwakkel, 2014), and disagreement in theories and conceptual frameworks underpinning the models (in problem articulation and conceptualization) (de Haan *et al.*, 2016; Quinn *et al.*, 2017). The further incorporation of these uncertainties within the computational process of modeling can enable more robust decision-making.

When exploratory modeling is used to investigate a wide range of assumptions through batch simulations, it can result in very large data outputs which need to be analyzed and understood in decision-making. Statistical and data-mining techniques can be used to analyze big data from exploratory modeling. However, current exploratory modeling approaches do not provide much guidance for how their outputs should be interpreted. Here a gap exists between results and decision-making (in policy evaluation), leading to another challenge, that is the ‘*limitations in communication and interpretation of the results*’. The visualization limitation in the communication of multi-dimensional data and the limited cognitive capacity of humans (i.e., model users and decision-makers) in examining the multiple dimensions of data at once can make the interpretation of the exploratory modeling results even more challenging. Understanding the results often requires techniques for viewing highly multi-dimensional data. The use of advanced visualization techniques (Brodlie *et al.*, 2012; Bryan *et al.*, 2016; Reed & Kollat, 2013; Woodruff *et al.*, 2013), which allow users to explore data graphically in multiple dimensions, can be a way to mitigate this challenge and assist in interpretation. One example is Kasprzyk *et al.* (2013) where they used Interactive Visual Analytics to support collaboration with users and to improve their ability to effectively analyze many decisions generated by an exploratory modeling approach. The use of data-mining methods such as clustering which summarizes multi-dimensional data into distinct groups is also another way to address this challenge (de Haan *et al.*, 2016; Gerst *et al.*, 2013; Guivarch *et al.*, 2016; Rozenberg *et al.*, 2014).

4.2 Managing complexity

Real-world human and natural systems are complex. Complex systems are often characterized as incorporating many parts, comprising causally interrelated elements within multiple social, technical, and economic dimensions (Bunge, 1997). While this holds true to the etymology of the term *complex*, systems and models can exhibit complexity yet look deceptively simple. The logistic map, a fully deterministic, one-variable, discrete, iterated equation, is a classic example. However, for certain values of its only parameter, it exhibits full-blown chaos (Stewart, 1989). In other words, many parts should not be thought of as a necessary condition for

complexity. What does seem to be a necessary condition for complexity is non-linearity. It is the non-linearity in the logistic map that is the source of its chaos and if a system of many parts is complex it is due to non-linear interactions, side-effects, and emergent features (Bunge, 2003) amongst those many parts. Given the complexity, these systems are typically hard to predict or explain directly in terms of the behavior of individual elements (de Haan, 2006). A great strength of exploratory modeling is in '*coping with systemic complexity*'. An exploratory approach enhances model formulation by making valid conclusions not necessarily from individually correct models of complex systems, but from an ensemble of different framings of these systems, for example with various interactions between elements and different agent rules. To illustrate, Pruyt and Kwakkel (2014) and Auping *et al.* (2016) have used exploratory modeling for investigating the implications of model (structural) complexity in energy sector and national security contexts, respectively. Real-world systems are also often characterized by a complex combination of decisions that requires a high level of performance for multiple (sometimes conflicting) objectives. Exploratory modeling can enable the investigation the diversity of decision alternatives (instead of a limited set) and capturing key trade-offs (Gold *et al.*, 2019; Mitchell, 2009; Singh *et al.*, 2015; Trindade *et al.*, 2017).

The cognitive complexity of testing various alternative assumptions and observing their consequences in the outcome space manually poses a significant barrier, in addition to the systemic complexity itself. Exploratory modeling can be helpful in dealing with this aspect of complexity in implementation too, by '*facilitating systematic experimentation*'. Exploratory modeling has adopted computational support such as the Python-based Exploratory Modeling Workbench (Kwakkel, 2017) and OpenMORDM (Hadka *et al.*, 2015) amongst other associated libraries (Hadjimichael *et al.*, 2020a; Trindade *et al.*, 2020), for the systematic assessment of assumptions and learning about model behavior in a multi-objective space. Exploratory modeling using these computational supports can enhance analytical capability through managing, tracing, and documenting many quantitative models, large datasets, and conceptual framings. Such computational support can help in quantifying the consequences of many assumptions for outcomes through experimenting in an automated process (Kwakkel, 2017). This can be a helpful feature in model formulation where modelers often experiment with assumptions in an ad hoc manner before they settle on their ultimate set of assumptions that constitute their model. For example, Kwakkel *et al.* (2015) and Fletcher *et al.* (2019) used exploratory modeling (policy search and stochastic dynamic programming) as a computational support to address the combinatorial problem in policy design arising from many ways in which decision alternatives can be sequenced over time and the rules that govern when new decisions are to be triggered in adaptive planning. In this way, exploratory modeling can also help in the uncertainty analysis of model behavior, contributing to the modeling process in policy evaluation.

While exploratory modeling approaches can help in coping with the complexity of systems and experimentation, they can still face some '*computational limitations in working with large-scale assessment models*'. These models often have extensive and complex structures, integrating many interacting components and agents to represent system processes. Examples can be found among established environmental models, such as energy and climate models, commonly used in global or regional integrated assessment (IPCC, 2018; UN, 2019). Complexity may be even greater in agent-based models, which are assumed to have a capacity to model and capture in detail the multiple interactions of human-natural systems (Bankes, 2002a, 2002b; Lempert, 2002). Agent-based models can feature a large number of input parameters for different classes of agents, which can significantly expand the size of the assumption space for a

model to search through (Moallemi & Köhler, 2019). Producing even a few scenarios with such models can sometimes take several days. Such a slow simulation process can impose a challenge for some of these large-scale models in adopting exploratory modeling that requires a wide exploration/search over various assumptions. One obvious approach to mitigate this challenge is the use of efficient algorithms, parallel processing, and high-performance computing (Bryan, 2013; Reed *et al.*, 2008; Zhao *et al.*, 2013). Another way is via the use of meta-models for screening and analyzing an ensemble of model behaviors and observing interesting model outcomes (Haasnoot *et al.*, 2014). This can lead to a multi-resolution model of a complex system with a high-level of abstraction which can be used initially to facilitate the exploratory modeling process. The full resolution model can then be used to investigate model behaviors of interest. Adaptive sampling can also be used to search the uncertainty space based on its likelihood of uncertainty estimation and the complexity of the likelihood surface of the uncertainty space; the complexity that results from the interaction of multiple uncertainty dimensions as well as the model structure (Blasone *et al.*, 2008; Islam & Pruyt, 2016; Khu & Werner, 2003).

5 Exploratory modeling with stakeholders

Policy agencies and science funding organizations increasingly require scientists and stakeholders (e.g., practitioners, policy/decision-makers, civil society, interest groups) to *co-create* the knowledge for dealing with the complex challenges of coupled human-natural systems (Game *et al.*, 2018; Mauser *et al.*, 2013; Moallemi *et al.*, 2020a; Moser, 2016; Norström *et al.*, 2020). Co-creation of knowledge has been discussed in the context of participatory modeling and decision-making (Halbe *et al.*, 2020; Halbe *et al.*, 2018; Jordan *et al.*, 2018; Voinov *et al.*, 2018). Within the context of exploratory modeling, several previous studies have discussed co-creation, implicitly or explicitly, through embedding stakeholder input into the iterative process of modeling and combining computational and human capabilities interactively (Eker *et al.*, 2017; Kasprzyk *et al.*, 2013; Lempert *et al.*, 2003; Moallemi & Malekpour, 2018; van Bruggen *et al.*, 2019). In the context of decision-making, they urged deliberation with analysis where model users can interact with the computational process, observe counterintuitive results based on a shared vision of the problem, and inform the improvement of results (National Research Council, 2009). Some recent studies also further investigated nuances of modeling social/psychological dimensions, discussing human factors (such as biases and hidden preferences) that shape decision-making (Moallemi *et al.*, 2020b; Zare *et al.*, 2020). Despite this growing interest, deliberation with analysis in exploratory modeling remains a black box and the co-creation of knowledge with stakeholder participation in the robust decision context remains a topic of lively debate (Alrøe & Noe, 2016; Döll & Romero-Lankao, 2017; Glynn *et al.*, 2017, 2018; Walker *et al.*, 2018). Learning from previous work (Landström *et al.*, 2011; Lane *et al.*, 2011) and building on the Mauser *et al.* (2013) framework for knowledge co-creation, we discuss some of the ways for stakeholder participation in exploratory modeling, aiming to contribute to better approaches for *socially* robust inference.

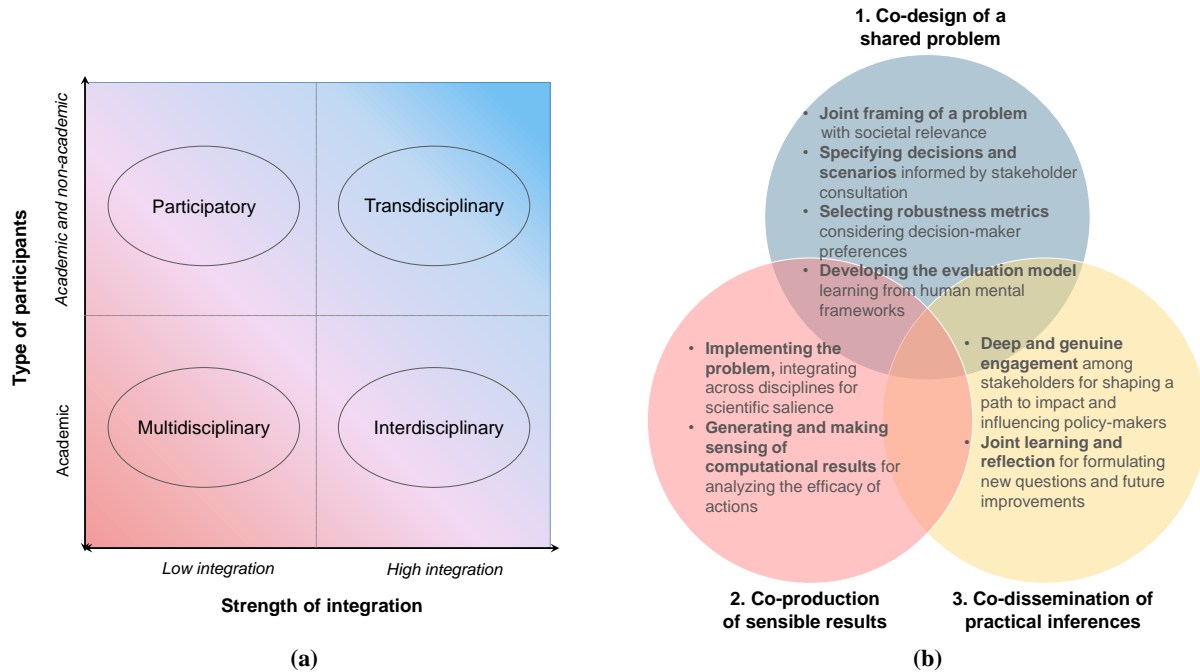


Figure 3. The co-creation of knowledge with stakeholders. (a) shows different forms of stakeholder participation, based on Tress *et al.* (2005). The color hue shows participation with diverse participant groups and a high integration of knowledge forms from various sources (blue) versus participation with narrow participant groups and a low integration (red); (b) shows the three ways for the co-creation of knowledge in exploratory modeling, with their varying forms of stakeholder participation.

Tress *et al.* (2005) argued that different forms of stakeholder participation can be imagined (see Figure 3a), varying based on the type of participants (who is involved?) and the strength of integration across research concepts (what is the diversity of incorporated language and forms of knowledge?). From these different forms, interdisciplinary and transdisciplinary research often involves a stronger integration compared to multidisciplinary and participatory approaches. There is also a wider and more inclusive incorporation of academics and non-academics (e.g., civil society, policy-makers, practitioners) in participatory and transdisciplinary research for enhancing legitimacy and accountability among stakeholders. Conversely, multidisciplinary and interdisciplinary aim to improve the consistency and salience of the research across scientific disciplines, and therefore often focus more on engagement with different academic communities (Mauser *et al.*, 2013; Tress *et al.*, 2005). We argue that exploratory modeling can learn from these approaches for the co-creation of knowledge to *co-design* a shared problem, *co-produce* sensible results for the problem, and *co-disseminate* robust sensible inferences (Figure 3b).

The co-design of a shared decision problem involves the joint framing of a pressing sustainability challenge from relevant societal sectors through *participatory* processes (e.g., workshops, brainstorming). Co-design also involves the translation of the real-world sustainability challenge into an abstract problem that can be analyzed with models. The required knowledge for the specification of problem components (i.e., decisions, scenarios, robustness metrics, models) can be obtained through the interaction of scientific methods with social contexts (Lempert *et al.*, 2003). For example, scientists and stakeholders can together identify a range of feasible candidate decisions (e.g., through SWOT analysis and multi-criteria decision

analysis) and influential but uncertain factors in future scenarios (e.g., participatory scenario development and scenario discovery). Depending on the confidence of stakeholder knowledge and agreement among different views, the decision and scenarios can be specified by human judgement *a priori* to analysis (de Neufville *et al.*, 2019) or in an iterative process where the initial list of pre-specified decisions are refined based on the feedback from the analytical results (Kasprzyk *et al.*, 2013). The selection of appropriate robustness metrics and models is also sensitive to stakeholder participation. There are different elicitation tools (Morris *et al.*, 2014; Reichert *et al.*, 2013) that can help in defining appropriate robustness metrics by obtaining knowledge of context (e.g., about the relevancy of absolute performance or regret measures) and decision-maker preferences (e.g., about preferred risk aversion level) (McPhail *et al.*, 2018). Eliciting mental models and assumptions of various academic and non-academic participants about underlying causal interactions of the problem can also help to delineate meaningful boundaries and develop relevant evaluation models in decision-making (Mayer *et al.*, 2017). Here the modeling literature has several examples of model development with stakeholders through conceptual and cognitive mapping (Gray *et al.*, 2012), system dynamics modeling (Zare *et al.*, 2019), and other participatory modeling approaches (Basco-Carrera *et al.*, 2017; Voinov, 2017).

The co-production of exploratory modeling results is about the generation of sensible and credible outcomes from the quantification of the costs and benefits, not necessarily in monetary terms, of various decisions under future scenarios. Co-production involves the interaction of *interdisciplinary* teams to integrate different methods in a way that best serves the problem at hand. The integration in exploratory modeling can be as simple as the independent applications of two methods and frameworks on the same problem and the comparative analysis of the results (Halim *et al.*, 2016). It can also be more sophisticated in design, from a sequential integration where the output from one is used as input to another (Glasgow *et al.*, 2018), to a full integration where new frameworks emerge from two-way interactions between multiple methods and frameworks (Watson & Kasprzyk, 2017). Co-production also involves the generation of computational experiments and making sense of the results of the experiments for analyzing the efficacy of various decisions and making trade-offs between multiple objectives. Collaborations among various scientific expertise can broaden perspectives and expand choices of suitable analytical (e.g., sampling and optimization) algorithms (Maier *et al.*, 2019; Reed *et al.*, 2013) and toolboxes for their implementation (Hadka *et al.*, 2015; Kwakkel, 2017).

The co-dissemination of exploratory modeling results aims to enhance the ownership and accountability of outcomes and helps to influence policymakers' decisions via deep and genuine engagement with stakeholders. This can be achieved through a *transdisciplinary* approach that brings scientific and stakeholder groups together for shaping a path to impact on the ground. Collaborative efforts between academics and non-academics can help in translating the abstract results into practical inferences, with an accessible and comprehensive language for different audiences. Interaction with these stakeholder groups, for example via role-playing games (d'Aquino & Bah, 2013), visual analytics (Reed & Kollat, 2013), and web applications (Nativi *et al.*, 2013), can enable joint learning and ongoing reflection of the results. This can also help to create new research questions and improve problem framings for the future, contributing to the iterative cycle of human deliberation with model-based analysis.

Future studies can further advance this discussion by translating it in the context of different decision-making frameworks and by implementing it in applications. Collaborating

with stakeholders with different characteristics, such as willingness to participate, strategic thinking maturity, and divergence of values, can pose practical limitations on knowledge co-creation that need to be addressed within the case studies (Hurlbert & Gupta, 2015; Jordan *et al.*, 2018; Smajgl & Ward, 2015).

6 Conclusions

There is inherent complexity in the interactions and processes in the sustainability of coupled human-natural systems, such as climate, land-use, energy, and water (Howells *et al.*, 2013). These systems are also surrounded by uncertainties arising from the multiple factors including long time-scales, spatial heterogeneity, environmental change versus natural variability, alternative theories and models of human-nature interactions, contextual contingencies, and contested views of stakeholders. The presence of complexity and deep uncertainty has challenged the relevance of conventional modeling approaches (which use prior information) for understanding the behavior of these systems and for informing decisions towards sustainability. Conventional approaches can prematurely close down the assumption space in the pursuit of a best-estimate scenario. Through this pre-mature closure, the modeler may also forego the ability to even assess how good the best-estimate scenario is and how robust inferences are. Exploratory modeling can address the challenges posed by complexity and deep uncertainty by modeling coupled human-natural systems under uncertainty and informing decision-making for sustainability by generating robust inferences. While exploratory modeling can face challenges in practice, such as computational limitations with large-scale assessment models and limitations on communications and interpretation of the results, it still offers great benefits to modeling and model-based decision-making. There is substantial potential for the further use of this approach by researchers and practitioners in new applications spanning multiple sustainability contexts. Our taxonomy can guide this wider adoption by illustrating the ways in which exploratory modeling can be used across different areas. We hope that the proposed taxonomy can be used as a benchmark framework for enhancing robust inferences about the impacts of global change on sustainability priorities through recognizing and implementing rival ways of modeling under uncertainty.

References

- Alrøe, H. F., & Noe, E. (2016). Sustainability assessment and complementarity. *Ecology and Society*, 21(1). doi: 10.5751/ES-08220-210130
- Auping, W. L., Pruyt, E., de Jong, S., & Kwakkel, J. H. (2016). The geopolitical impact of the shale revolution: Exploring consequences on energy prices and rentier states. *Energy Policy*, 98, 390-399.
- Babovic, F., & Mijic, A. (2019). The development of adaptation pathways for the long-term planning of urban drainage systems. *Journal of Flood Risk Management*, 0(0), e12538. doi: 10.1111/jfr3.12538
- Bankes, S. (1993). Exploratory modeling for policy analysis. *Operations Research*, 41(3), 435-449.
- Bankes, S., Walker, W. E., & Kwakkel, J. H. (2013). Exploratory Modeling and Analysis. In S. I. Gass & M. C. Fu (Eds.), *Encyclopedia of Operations Research and Management Science* (3rd ed., pp. 532-537). New York: Springer.
- Bankes, S. C. (2002a). Agent-based modeling: A revolution? *Proceedings of the National Academy of Sciences*, 99(suppl 3), 7199-7200. doi: 10.1073/pnas.072081299
- Bankes, S. C. (2002b). Tools and techniques for developing policies for complex and uncertain systems. *Proceedings of the National Academy of Sciences*, 99(suppl 3), 7263-7266. doi: 10.1073/pnas.092081399
- Bartholomew, E., & Kwakkel, J. H. (2020). On considering robustness in the search phase of Robust Decision Making: A comparison of Many-Objective Robust Decision Making, multi-scenario Many-Objective

- Robust Decision Making, and Many Objective Robust Optimization. *Environmental Modelling & Software*, 127, 104699. doi: <https://doi.org/10.1016/j.envsoft.2020.104699>
- Basco-Carrera, L., van Beek, E., Jonoski, A., Benítez-Ávila, C., & Pj Guntoro, F. X. (2017). Collaborative Modelling for Informed Decision Making and Inclusive Water Development. *Water Resources Management*, 31(9), 2611-2625. doi: 10.1007/s11269-017-1647-0
- Ben-Haim, Y. (2006). *Info-Gap Decision Theory: Decisions Under Severe Uncertainty*. London, UK: Academic Press.
- Ben-Haim, Y. (2019). Info-Gap Decision Theory (IG). In V. A. W. J. Marchau, W. E. Walker, P. J. T. M. Bloemen & S. W. Popper (Eds.), *Decision Making under Deep Uncertainty: From Theory to Practice* (pp. 93-115). Cham: Springer International Publishing.
- Berntsen, P. B., & Trutnevyte, E. (2017). Ensuring diversity of national energy scenarios: Bottom-up energy system model with Modeling to Generate Alternatives. *Energy*, 126, 886-898. doi: <https://doi.org/10.1016/j.energy.2017.03.043>
- Bijl, D. L., Bogaart, P. W., Dekker, S. C., Stehfest, E., de Vries, B. J. M., & van Vuuren, D. P. (2017). A physically-based model of long-term food demand. *Global Environmental Change*, 45, 47-62. doi: <https://doi.org/10.1016/j.gloenvcha.2017.04.003>
- Bilskie, M. V., Hagen, S. C., Alizad, K., Medeiros, S. C., Passeri, D. L., Needham, H. F., & Cox, A. (2016). Dynamic simulation and numerical analysis of hurricane storm surge under sea level rise with geomorphologic changes along the northern Gulf of Mexico. *Earth's Future*, 4(5), 177-193. doi: 10.1002/2015EF000347
- Blasone, R.-S., Madsen, H., & Rosbjerg, D. (2008). Uncertainty assessment of integrated distributed hydrological models using GLUE with Markov chain Monte Carlo sampling. *Journal of Hydrology*, 353(1), 18-32.
- Boero, R., & Squazzoni, F. (2005). Does empirical embeddedness matter? Methodological issues on agent-based models for analytical social science. *Journal of Artificial Societies and Social Simulation*, 8(4).
- Borgomeo, E., Hall, J. W., Fung, F., Watts, G., Colquhoun, K., & Lambert, C. (2014). Risk-based water resources planning: Incorporating probabilistic nonstationary climate uncertainties. *Water Resour. Res.*, 50, 6850.
- Brodlie, K., Allendes Osorio, R., & Lopes, A. (2012). A Review of Uncertainty in Data Visualization. In J. Dill, R. Earnshaw, D. Kasik, J. Vince & P. C. Wong (Eds.), *Expanding the Frontiers of Visual Analytics and Visualization* (pp. 81-109). London: Springer London.
- Brown, C., Ghile, Y., Laverty, M., & Li, K. (2012). Decision Scaling: Linking bottom-up vulnerability analysis with climate projections in the water sector. *Water Resources Research*, 48(9).
- Bryan, B. A. (2013). High-performance computing tools for the integrated assessment and modelling of social-ecological systems. *Environmental Modelling & Software*, 39, 295-303. doi: <https://doi.org/10.1016/j.envsoft.2012.02.006>
- Bryan, B. A., Nolan, M., McKellar, L., Connor, J. D., Newth, D., Harwood, T., . . . Hatfield-Dodds, S. (2016). Land-use and sustainability under intersecting global change and domestic policy scenarios: Trajectories for Australia to 2050. *Global Environmental Change*, 38, 130-152. doi: <https://doi.org/10.1016/j.gloenvcha.2016.03.002>
- Bryant, B. P., & Lempert, R. J. (2010). Thinking inside the box: A participatory, computer-assisted approach to scenario discovery. *Technological Forecasting and Social Change*, 77(1), 34-49.
- Bunge, M. (2003). *Emergence and Convergence: Qualitative Novelty and the Unity of Knowledge*: University of Toronto Press Incorporated, Toronto.
- Bunge, M. A. (1997). Mechanism and Explanation. *Philosophy of the Social Sciences*, 27, 410-465.
- Carlsen, H., Lempert, R., Wikman-Svahn, P., & Schweizer, V. (2016). Choosing small sets of policy-relevant scenarios by combining vulnerability and diversity approaches. *Environmental Modelling & Software*, 84, 155-164. doi: <https://doi.org/10.1016/j.envsoft.2016.06.011>
- Castelletti, A., Yajima, H., Giuliani, M., Soncini-Sessa, R., & Weber, E. (2014). Planning the Optimal Operation of a Multioutlet Water Reservoir with Water Quality and Quantity Targets. *Journal of Water Resources Planning and Management*, 140(4), 496-510. doi: 10.1061/(ASCE)WR.1943-5452.0000348
- d'Aquino, P., & Bah, A. (2013). A Participatory Modeling Process to Capture Indigenous Ways of Adaptability to Uncertainty: Outputs From an Experiment in West African Drylands. *Ecology and Society*, 18(4). doi: 10.5751/ES-05876-180416
- de Haan, F. J. (2006). How emergence arises. *Ecological Complexity*, 3(4), 293-301. doi: <http://dx.doi.org/10.1016/j.ecocom.2007.02.003>

- de Haan, F. J., Rogers, B. C., Brown, R. R., & Deletic, A. (2016). Many roads to Rome: The emergence of pathways from patterns of change through exploratory modelling of sustainability transitions. *Environmental Modelling & Software*, *85*, 279-292. doi: <http://dx.doi.org/10.1016/j.envsoft.2016.05.019>
- de Neufville, R., Smet, K., Cardin, M.-A., & Ranjbar-Bourani, M. (2019). Engineering Options Analysis (EOA): Applications. In V. A. W. J. Marchau, W. E. Walker, P. J. T. M. Bloemen & S. W. Popper (Eds.), *Decision Making under Deep Uncertainty: From Theory to Practice* (pp. 223-252). Cham: Springer International Publishing.
- Dessai, S., & Hulme, M. (2007). Assessing the robustness of adaptation decisions to climate change uncertainties: A case study on water resources management in the East of England. *Global Environmental Change*, *17*(1), 59-72. doi: <https://doi.org/10.1016/j.gloenvcha.2006.11.005>
- Dewar, J. A., Builder, C. H., Hix, W. M., & Levin, M. H. (1993). *Assumption-Based Planning: a planning tool for very uncertain times*. RAND. Santa Monica, USA.
- Di Baldassarre, G., Brandimarte, L., & Beven, K. (2016). The seventh facet of uncertainty: wrong assumptions, unknowns and surprises in the dynamics of human–water systems. *Hydrological Sciences Journal*, *61*(9), 1748-1758. doi: 10.1080/02626667.2015.1091460
- Doelman, J. C., Stehfest, E., Tabeau, A., van Meijl, H., Lassaletta, L., Gernaat, D. E. H. J., . . . van Vuuren, D. P. (2018). Exploring SSP land-use dynamics using the IMAGE model: Regional and gridded scenarios of land-use change and land-based climate change mitigation. *Global Environmental Change*, *48*, 119-135. doi: <https://doi.org/10.1016/j.gloenvcha.2017.11.014>
- Döll, P., & Romero-Lankao, P. (2017). How to embrace uncertainty in participatory climate change risk management—A roadmap. *Earth's Future*, *5*(1), 18-36. doi: 10.1002/2016EF000411
- Eker, S., & Kwakkel, J. H. (2018). Including robustness considerations in the search phase of Many-Objective Robust Decision Making. *Environmental Modelling & Software*, *105*, 201-216. doi: <https://doi.org/10.1016/j.envsoft.2018.03.029>
- Eker, S., Reese, G., & Obersteiner, M. (2019). Modelling the drivers of a widespread shift to sustainable diets. *Nature sustainability*. doi: 10.1038/s41893-019-0331-1
- Eker, S., & van Daalen, E. (2015). A model-based analysis of biomethane production in the Netherlands and the effectiveness of the subsidization policy under uncertainty. *Energy Policy*, *82*, 178-196. doi: <http://dx.doi.org/10.1016/j.enpol.2015.03.019>
- Eker, S., van Daalen, E., & Thissen, W. (2017). Incorporating stakeholder perspectives into model-based scenarios: Exploring the futures of the Dutch gas sector. *Futures*, *93*(Supplement C), 27-43. doi: <https://doi.org/10.1016/j.futures.2017.08.002>
- Fischer, G., Shah, M., N. Tubiello, F., & van Velhuizen, H. (2005). Socio-economic and climate change impacts on agriculture: an integrated assessment, 1990–2080. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *360*(1463), 2067-2083. doi: 10.1098/rstb.2005.1744
- Fletcher, S., Lickley, M., & Strzepek, K. (2019). Learning about climate change uncertainty enables flexible water infrastructure planning. *Nature Communications*, *10*(1), 1782. doi: 10.1038/s41467-019-09677-x
- Funtowicz, S., & Ravetz, J. (1990). Post-normal science: a new science for new times. *Scientific European*, *266*(10), 20-22.
- Game, E. T., Tallis, H., Olander, L., Alexander, S. M., Busch, J., Cartwright, N., . . . Sutherland, W. J. (2018). Cross-discipline evidence principles for sustainability policy. *Nature sustainability*, *1*(9), 452-454. doi: 10.1038/s41893-018-0141-x
- Gao, L., & Bryan, B. A. (2017). Finding pathways to national-scale land-sector sustainability. *Nature*, *544*, 217. doi: 10.1038/nature21694
- Gao, L., Bryan, B. A., Nolan, M., Connor, J. D., Song, X., & Zhao, G. (2016). Robust global sensitivity analysis under deep uncertainty via scenario analysis. *Environmental Modelling & Software*, *76*, 154-166. doi: <https://doi.org/10.1016/j.envsoft.2015.11.001>
- Gerst, M. D., Wang, P., & Borsuk, M. E. (2013). Discovering plausible energy and economic futures under global change using multidimensional scenario discovery. *Environmental Modelling & Software*, *44*, 76-86. doi: <http://dx.doi.org/10.1016/j.envsoft.2012.09.001>
- Giudici, F., Castelletti, A., Giuliani, M., & Maier, H. R. (2020). An active learning approach for identifying the smallest subset of informative scenarios for robust planning under deep uncertainty. *Environmental Modelling & Software*, *127*, 104681. doi: <https://doi.org/10.1016/j.envsoft.2020.104681>
- Giuliani, M., & Castelletti, A. (2016). Is robustness really robust? How different definitions of robustness impact decision-making under climate change. *Climatic Change*, *135*(3), 409-424. doi: 10.1007/s10584-015-1586-9

- Giuliani, M., Herman, J. D., Castelletti, A., & Reed, P. (2014). Many-objective reservoir policy identification and refinement to reduce policy inertia and myopia in water management. *Water Resources Research*, 50(4), 3355-3377. doi: 10.1002/2013WR014700
- Glasgow, S. M., Perkins, Z. B., Tai, N. R. M., Brohi, K., & Vasilakis, C. (2018). Development of a discrete event simulation model for evaluating strategies of red blood cell provision following mass casualty events. *European Journal of Operational Research*, 270(1), 362-374. doi: <https://doi.org/10.1016/j.ejor.2018.03.008>
- Glynn, P. D., Voinov, A. A., Shapiro, C. D., & White, P. A. (2017). From data to decisions: Processing information, biases, and beliefs for improved management of natural resources and environments. *Earth's Future*, 5(4), 356-378. doi: doi:10.1002/2016EF000487
- Glynn, P. D., Voinov, A. A., Shapiro, C. D., & White, P. A. (2018). Response to Comment by Walker et al. on "From Data to Decisions: Processing Information, Biases, and Beliefs for Improved Management of Natural Resources and Environments". *Earth's Future*, 6(5), 762-769. doi: 10.1002/2018EF000819
- Gold, D. F., Reed, P. M., Trindade, B. C., & Characklis, G. W. (2019). Identifying Actionable Compromises: Navigating Multi-City Robustness Conflicts to Discover Cooperative Safe Operating Spaces for Regional Water Supply Portfolios. *Water Resources Research*, n/a(n/a). doi: 10.1029/2019WR025462
- Gray, S., Chan, A., Clark, D., & Jordan, R. (2012). Modeling the integration of stakeholder knowledge in social-ecological decision-making: Benefits and limitations to knowledge diversity. *Ecological Modelling*, 229, 88-96. doi: <https://doi.org/10.1016/j.ecolmodel.2011.09.011>
- Groves, D. G., Molina-Perez, E., Bloom, E., & Fischbach, J. R. (2019). Robust Decision Making (RDM): Application to Water Planning and Climate Policy. In Marchau V., Walker W., Bloemen P. & P. S. (Eds.), *Decision Making under Deep Uncertainty*: Springer.
- Grundy, M. J., Bryan, B. A., Nolan, M., Battaglia, M., Hatfield-Dodds, S., Connor, J. D., & Keating, B. A. (2016). Scenarios for Australian agricultural production and land use to 2050. *Agricultural Systems*, 142, 70-83. doi: <https://doi.org/10.1016/j.agsy.2015.11.008>
- Guivarch, C., Lempert, R., & Trutnevyte, E. (2017). Scenario techniques for energy and environmental research: An overview of recent developments to broaden the capacity to deal with complexity and uncertainty. *Environmental Modelling & Software*, 97, 201-210. doi: <http://dx.doi.org/10.1016/j.envsoft.2017.07.017>
- Guivarch, C., Rozenberg, J., & Schweizer, V. (2016). The diversity of socio-economic pathways and CO2 emissions scenarios: Insights from the investigation of a scenarios database. *Environmental Modelling & Software*, 80, 336-353. doi: <http://dx.doi.org/10.1016/j.envsoft.2016.03.006>
- Haasnoot, M., Kwakkel, J. H., Walker, W. E., & ter Maat, J. (2013). Dynamic adaptive policy pathways: A method for crafting robust decisions for a deeply uncertain world. *Global Environmental Change*, 23(2), 485-498. doi: <http://dx.doi.org/10.1016/j.gloenvcha.2012.12.006>
- Haasnoot, M., van 't Klooster, S., & van Alphen, J. (2018). Designing a monitoring system to detect signals to adapt to uncertain climate change. *Global Environmental Change*, 52, 273-285. doi: <https://doi.org/10.1016/j.gloenvcha.2018.08.003>
- Haasnoot, M., van Deursen, W. P. A., Guillaume, J. H. A., Kwakkel, J. H., van Beek, E., & Middelkoop, H. (2014). Fit for purpose? Building and evaluating a fast, integrated model for exploring water policy pathways. *Environmental Modelling & Software*, 60(Supplement C), 99-120. doi: <https://doi.org/10.1016/j.envsoft.2014.05.020>
- Hadjimichael, A., Gold, D., Hadka, D., & Reed, P. (2020a). Rhodium: Python Library for Many-Objective Robust Decision Making and Exploratory Modeling. *Journal of Open Research Software*, 8(1), 12. doi: <http://doi.org/10.5334/jors.293>
- Hadjimichael, A., Quinn, J., Wilson, E., Reed, P., Basdekas, L., Yates, D., & Garrison, M. (2020b). Defining robustness, vulnerabilities, and consequential scenarios for diverse stakeholder interests in institutionally complex river basins. *Earth's Future*, n/a(n/a), e2020EF001503. doi: 10.1029/2020EF001503
- Hadka, D., Herman, J., Reed, P., & Keller, K. (2015). An open source framework for many-objective robust decision making. *Environmental Modelling & Software*, 74, 114-129. doi: <https://doi.org/10.1016/j.envsoft.2015.07.014>
- Halbe, J., Holtz, G., & Ruutu, S. (2020). Participatory modeling for transition governance: Linking methods to process phases. *Environmental Innovation and Societal Transitions*, 35, 60-76. doi: <https://doi.org/10.1016/j.eist.2020.01.008>
- Halbe, J., Pahl-Wostl, C., & Adamowski, J. (2018). A methodological framework to support the initiation, design and institutionalization of participatory modeling processes in water resources management. *Journal of Hydrology*, 556, 701-716. doi: <https://doi.org/10.1016/j.jhydrol.2017.09.024>

- Halim, R. A., Kwakkel, J. H., & Tavasszy, L. A. (2016). A scenario discovery study of the impact of uncertainties in the global container transport system on European ports. *Futures*, *81*, 148-160. doi: <http://dx.doi.org/10.1016/j.futures.2015.09.004>
- Hall, J. W., Harvey, H., & Manning, L. J. (2019). Adaptation thresholds and pathways for tidal flood risk management in London. *Climate Risk Management*, *24*, 42-58. doi: <https://doi.org/10.1016/j.crm.2019.04.001>
- Hamarat, C., Kwakkel, J. H., & Pruyt, E. (2013). Adaptive Robust Design under deep uncertainty. *Technological Forecasting and Social Change*, *80*(3), 408-418. doi: <http://dx.doi.org/10.1016/j.techfore.2012.10.004>
- Hamarat, C., Kwakkel, J. H., Pruyt, E., & Loonen, E. T. (2014). An exploratory approach for adaptive policymaking by using multi-objective robust optimization. *Simulation Modelling Practice and Theory*, *46*, 25-39. doi: <http://dx.doi.org/10.1016/j.simpat.2014.02.008>
- Helgeson, C. (2020). Structuring Decisions Under Deep Uncertainty. *Topoi*, *39*(2), 257-269. doi: 10.1007/s11245-018-9584-y
- Herman, J. D., Quinn, J. D., Steinschneider, S., Giuliani, M., & Fletcher, S. (2020). Climate Adaptation as a Control Problem: Review and Perspectives on Dynamic Water Resources Planning Under Uncertainty. *Water Resources Research*, *56*(2), e24389. doi: 10.1029/2019WR025502
- Herman, J. D., Reed, P. M., Zeff, H. B., & Characklis, G. W. (2015). How should robustness be defined for water systems planning under change? *Journal of Water Resources Planning and Management*, *141*(10), 04015012.
- Herman, J. D., Zeff, H. B., Lamontagne, J. R., Reed, P. M., & Characklis, G. W. (2016). Synthetic Drought Scenario Generation to Support Bottom-Up Water Supply Vulnerability Assessments. *Journal of Water Resources Planning and Management*, *142*(11), 04016050. doi: 10.1061/(ASCE)WR.1943-5452.0000701
- Herman, J. D., Zeff, H. B., Reed, P. M., & Characklis, G. W. (2014). Beyond optimality: Multistakeholder robustness tradeoffs for regional water portfolio planning under deep uncertainty. *Water Resour. Res.*, *50*, 7692.
- Hodges, J. S. (1991). Six (or so) things you can do with a bad model. *Operations Research*, *39*(3), 355-365.
- Hodges, J. S., & Dewar, J. A. (1992). *Is it You or Your Model Talking? A Framework for Model Validation*. RAND Corporation. Santa Monica, CA, USA. Retrieved from <http://www.rand.org/pubs/reports/2006/R4114.pdf>
- Howells, M., Hermann, S., Welsch, M., Bazilian, M., Segerström, R., Alfstad, T., . . . Ramma, I. (2013). Integrated analysis of climate change, land-use, energy and water strategies. *Nature Climate Change*, *3*(7), 621-626. doi: 10.1038/nclimate1789
- Hurlbert, M., & Gupta, J. (2015). The split ladder of participation: A diagnostic, strategic, and evaluation tool to assess when participation is necessary. *Environmental Science & Policy*, *50*, 100-113. doi: <https://doi.org/10.1016/j.envsci.2015.01.011>
- Huskova, I., Matrosov, E. S., Harou, J. J., Kasprzyk, J. R., & Lambert, C. (2016). Screening robust water infrastructure investments and their trade-offs under global change: A London example. *Global Environmental Change*, *41*, 216-227. doi: <https://doi.org/10.1016/j.gloenvcha.2016.10.007>
- IPBES. (2019). *Global Assessment Report on Biodiversity and Ecosystem Services*. the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES). Paris, France. Retrieved from <https://www.ipbes.net/global-assessment-report-biodiversity-ecosystem-services>
- IPCC. (2018). *Global Warming of 1.5 °C: An IPCC special report on the impacts of global warming of 1.5 °C*. Intergovernmental Panel on Climate Change. Retrieved from <http://www.ipcc.ch/report/sr15/>
- IPCC. (2019). *Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems*. The Intergovernmental Panel on Climate Change (IPCC). Retrieved from <https://www.ipcc.ch/report/srcl/>
- Islam, T., & Pruyt, E. (2016). Scenario generation using adaptive sampling: The case of resource scarcity. *Environmental Modelling & Software*, *79*(Supplement C), 285-299. doi: <https://doi.org/10.1016/j.envsoft.2015.09.014>
- Isley, S. C., Lempert, R. J., Popper, S. W., & Vardavas, R. (2015). The effect of near-term policy choices on long-term greenhouse gas transformation pathways. *Global Environmental Change*, *34*, 147-158. doi: <https://doi.org/10.1016/j.gloenvcha.2015.06.008>
- JGCRI. (2017). *GCAM v4.3 documentation: Global change assessment model (GCAM)*. The Joint Global Change Research Institute (JGCRI).

- Jordan, R., Gray, S., Zellner, M., Glynn, P. D., Voinov, A., Hedelin, B., . . . National Socio-Environmental Synthesis Center Participatory Modeling Pursuit Working, G. (2018). Twelve Questions for the Participatory Modeling Community. *Earth's Future*, 6(8), 1046-1057. doi: 10.1029/2018EF000841
- Kasprzyk, J. R., Nataraj, S., Reed, P. M., & Lempert, R. J. (2013). Many objective robust decision making for complex environmental systems undergoing change. *Environmental Modelling & Software*, 42, 55-71. doi: <http://dx.doi.org/10.1016/j.envsoft.2012.12.007>
- Kasprzyk, J. R., Reed, P. M., Kirsch, B. R., & Characklis, G. W. (2009). Managing population and drought risks using many-objective water portfolio planning under uncertainty. *Water Resources Research*, 45(12). doi: 10.1029/2009WR008121
- Khatami, S., Peel, M. C., Peterson, T. J., & Western, A. W. (2019). Equifinality and Flux Mapping: a new approach to model evaluation and process representation under uncertainty. *Water Resources Research*, 0(ja). doi: 10.1029/2018WR023750
- Khatami, S., Peterson, T., Peel, M., & Western, A. (2020). Evaluating Catchment Models as Multiple Working Hypotheses: on the Role of Error Metrics, Parameter Sampling, Model Structure, and Data Information Content. *Earth and Space Science Open Archive*. doi: <https://doi.org/10.1002/essoar.10504066.1>
- Khazaei, B., Khatami, S., Alemohammad, S. H., Rashidi, L., Wu, C., Madani, K., . . . Aghakouchak, A. (2019). Climatic or regionally induced by humans? Tracing hydro-climatic and land-use changes to better understand the Lake Urmia tragedy. *Journal of Hydrology*, 569, 203-217. doi: <https://doi.org/10.1016/j.jhydrol.2018.12.004>
- Khu, S.-T., & Werner, M. G. (2003). Reduction of Monte-Carlo simulation runs for uncertainty estimation in hydrological modelling. *Hydrology and Earth System Sciences Discussions*, 7(5), 680-692.
- Knight, F. H. (1921). Risk uncertainty and profit. Boston, MA: Houghton Mifflin Company.
- Kollat, J. B., & Reed, P. M. (2006). Comparing state-of-the-art evolutionary multi-objective algorithms for long-term groundwater monitoring design. *Adv. Water Resour.*, 29, 792.
- Kwakkel, J., Haasnoot, M., & Walker, W. (2015). Developing dynamic adaptive policy pathways: A computer-assisted approach for developing adaptive strategies for a deeply uncertain world. *Climatic Change*, 132, 373.
- Kwakkel, J. H. (2017). The Exploratory Modeling Workbench: An open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making. *Environmental Modelling & Software*, 96, 239-250. doi: <http://dx.doi.org/10.1016/j.envsoft.2017.06.054>
- Kwakkel, J. H. (2019). A generalized many-objective optimization approach for scenario discovery. *FUTURES & FORESIGHT SCIENCE*, 1(2), e8. doi: 10.1002/ffo2.8
- Kwakkel, J. H., & Haasnoot, M. (2019). Supporting DMDU: A Taxonomy of Approaches and Tools. In V. A. W. J. Marchau, W. E. Walker, P. Bloemen & S. Popper (Eds.), *Decision Making Under Deep Uncertainty – From Theory to Practice*: Springer.
- Kwakkel, J. H., Walker, W. E., & Marchau, V. A. W. J. (2010). Adaptive airport strategic planning. *European Journal of Transport and Infrastructure Research*, 10, 249-273.
- Lamontagne, J. R., Reed, P. M., Link, R., Calvin, K. V., Clarke, L. E., & Edmonds, J. A. (2018). Large Ensemble Analytic Framework for Consequence-Driven Discovery of Climate Change Scenarios. 6(3), 488-504. doi: 10.1002/2017EF000701
- Lamontagne, J. R., Reed, P. M., Marangoni, G., Keller, K., & Garner, G. G. (2019). Robust abatement pathways to tolerable climate futures require immediate global action. *Nature Climate Change*, 9, 290-294. doi: 10.1038/s41558-019-0426-8
- Landström, C., Whatmore, S. J., Lane, S. N., Odoni, N. A., Ward, N., & Bradley, S. (2011). Coproducing flood risk knowledge: redistributing expertise in critical 'participatory modelling'. *Environment and Planning A*, 43(7), 1617-1633.
- Lane, S. N., Odoni, N., Landström, C., Whatmore, S. J., Ward, N., & Bradley, S. (2011). Doing flood risk science differently: an experiment in radical scientific method. *Transactions of the Institute of British Geographers*, 36(1), 15-36. doi: 10.1111/j.1475-5661.2010.00410.x
- Lempert, R. J. (2002). A new decision sciences for complex systems. *Proceedings of the National Academy of Sciences*, 99(suppl 3), 7309-7313. doi: 10.1073/pnas.082081699
- Lempert, R. J. (2019). Robust Decision Making (RDM). In V. Marchau, W. Walker, P. Bloemen & S. Popper (Eds.), *Decision Making under Deep Uncertainty: From Theory to Practice* (pp. 23-51). Cham: Springer International Publishing.
- Lempert, R. J., Bryant, B. P., & Bankes, S. C. (2008). Comparing algorithms for scenario discovery. *RAND, Santa Monica, CA*.

- Lempert, R. J., & Collins, M. T. (2007). Managing the risk of uncertain threshold responses: comparison of robust, optimum, and precautionary approaches. *Risk Analysis*, 27(4), 1009-1026.
- Lempert, R. J., & Groves, D. G. (2010). Identifying and evaluating robust adaptive policy responses to climate change for water management agencies in the American west. *Technol. Forecast. Soc.*, 77, 960.
- Lempert, R. J., Kalra, N., Peyraud, S., Mao, Z., Tan, S. B., Cira, D., & Lotsch, A. (2013). *Ensuring Robust Flood Risk Management in Ho Chi Minh City*. Policy Research Working Paper 6465. World Bank.
- Lempert, R. J., Popper, S. W., & Bankes, S. C. (2003). *Shaping the next one hundred years: new methods for quantitative, long-term policy analysis*: Rand Corporation.
- Maier, H. R., Guillaume, J. H. A., van Delden, H., Riddell, G. A., Haasnoot, M., & Kwakkel, J. H. (2016). An uncertain future, deep uncertainty, scenarios, robustness and adaptation: How do they fit together? *Environmental Modelling & Software*, 81, 154-164. doi: <http://dx.doi.org/10.1016/j.envsoft.2016.03.014>
- Maier, H. R., Razavi, S., Kapelan, Z., Matott, L. S., Kasprzyk, J., & Tolson, B. A. (2019). Introductory overview: Optimization using evolutionary algorithms and other metaheuristics. *Environmental Modelling & Software*, 114, 195-213. doi: <https://doi.org/10.1016/j.envsoft.2018.11.018>
- Malek, K., Reed, P., Adam, J., Karimi, T., & Brady, M. (2020). Water rights shape crop yield and revenue volatility tradeoffs for adaptation in snow dependent systems. *Nature Communications*, 11(1), 3473. doi: 10.1038/s41467-020-17219-z
- Marcos-Martinez, R., Bryan, B. A., Schwabe, K. A., Connor, J. D., & Law, E. A. (2018). Forest transition in developed agricultural regions needs efficient regulatory policy. *Forest Policy and Economics*, 86, 67-75. doi: <https://doi.org/10.1016/j.forpol.2017.10.021>
- Mausser, W., Klepper, G., Rice, M., Schmalzbauer, B. S., Hackmann, H., Leemans, R., & Moore, H. (2013). Transdisciplinary global change research: the co-creation of knowledge for sustainability. *Current Opinion in Environmental Sustainability*, 5(3), 420-431. doi: <https://doi.org/10.1016/j.cosust.2013.07.001>
- Mayer, L. A., Loa, K., Cwik, B., Tuana, N., Keller, K., Gonnerman, C., . . . Lempert, R. J. (2017). Understanding scientists' computational modeling decisions about climate risk management strategies using values-informed mental models. *Global Environmental Change*, 42, 107-116. doi: <https://doi.org/10.1016/j.gloenvcha.2016.12.007>
- McPhail, C., Maier, H. R., Kwakkel, J. H., Giuliani, M., Castelletti, A., & Westra, S. (2018). Robustness metrics: How are they calculated, when should they be used and why do they give different results? *Earth's Future*, n/a-n/a. doi: 10.1002/2017EF000649
- McPhail, C., Maier, H. R., Westra, S., Kwakkel, J. H., & van der Linden, L. (2020). Impact of scenario selection on robustness. *Water Resources Research*, n/a(n/a), e2019WR026515. doi: 10.1029/2019WR026515
- Mercure, J.-F., Pollitt, H., Bassi, A. M., Viñuales, J. E., & Edwards, N. R. (2016). Modelling complex systems of heterogeneous agents to better design sustainability transitions policy. *Global Environmental Change*, 37, 102-115. doi: <https://doi.org/10.1016/j.gloenvcha.2016.02.003>
- Mitchell, S. D. (2009). *Unsimple truths: Science, complexity, and policy*. USA: University of Chicago Press.
- Moallemi, E. A., de Haan, F., Kwakkel, J., & Aye, L. (2017). Narrative-informed exploratory analysis of energy transition pathways: A case study of India's electricity sector. *Energy Policy*, 110, 271-287. doi: <https://doi.org/10.1016/j.enpol.2017.08.019>
- Moallemi, E. A., Elsworth, S., & Ryan, M. (2018). Model-based multi-objective decision making under deep uncertainty from a multi-method design lens. *Simulation Modelling Practice & Theory*, 84, 232-250. doi: <https://doi.org/10.1016/j.simpat.2018.02.009>
- Moallemi, E. A., & Köhler, J. (2019). Coping with uncertainties of sustainability transitions using exploratory modelling: The case of the MATISSE model and the UK's mobility sector. *Environmental Innovation and Societal Transitions*, 33, 61-83. doi: <https://doi.org/10.1016/j.eist.2019.03.005>
- Moallemi, E. A., & Malekpour, S. (2018). A participatory exploratory modelling approach for long-term planning in energy transitions. *Energy Research & Social Science*, 35, 205-216. doi: <https://doi.org/10.1016/j.erss.2017.10.022>
- Moallemi, E. A., Malekpour, S., Hadjikakou, M., Raven, R., Szetey, K., Ningrum, D., . . . Bryan, B. A. (2020a). Achieving the Sustainable Development Goals requires transdisciplinary innovation at the local scale. *One Earth*. doi: 10.1016/j.oneear.2020.08.006
- Moallemi, E. A., Zare, F., Reed, P. M., Elsworth, S., Ryan, M. J., & Bryan, B. A. (2020b). Structuring and evaluating decision support processes to enhance the robustness of complex human-natural systems. *Environmental Modelling & Software*, 123, 1045-1051. doi: <https://doi.org/10.1016/j.envsoft.2019.104551>
- Morgan, M. G., Henrion, M., & Small, M. (1990). *Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy analysis*. New York: Cambridge University Press.

- Morris, D. E., Oakley, J. E., & Crowe, J. A. (2014). A web-based tool for eliciting probability distributions from experts. *Environmental Modelling & Software*, *52*, 1-4. doi: <https://doi.org/10.1016/j.envsoft.2013.10.010>
- Moser, S. C. (2016). Can science on transformation transform science? Lessons from co-design. *Current Opinion in Environmental Sustainability*, *20*, 106-115. doi: <https://doi.org/10.1016/j.cosust.2016.10.007>
- National Research Council. (2009). *Informing decisions in a changing climate*: National Academies Press.
- Nativi, S., Mazzetti, P., & Geller, G. N. (2013). Environmental model access and interoperability: The GEO Model Web initiative. *Environmental Modelling & Software*, *39*, 214-228. doi: <https://doi.org/10.1016/j.envsoft.2012.03.007>
- Nazemi, A., Wheeler, H. S., Chun, K. P., & Elshorbagy, A. (2013). A stochastic reconstruction framework for analysis of water resource system vulnerability to climate-induced changes in river flow regime. *Water Resour. Res.*, *49*, 291.
- Norström, A. V., Cvitanovic, C., Löf, M. F., West, S., Wyborn, C., Balvanera, P., . . . Österblom, H. (2020). Principles for knowledge co-production in sustainability research. *Nature sustainability*. doi: 10.1038/s41893-019-0448-2
- Obersteiner, M., Walsh, B., Frank, S., Havlík, P., Cantele, M., Liu, J., . . . van Vuuren, D. (2016). Assessing the land resource–food price nexus of the Sustainable Development Goals. *Science Advances*, *2*(9), e1501499. doi: 10.1126/sciadv.1501499
- Oddo, P. C., Lee, B. S., Garner, G. G., Srikrishnan, V., Reed, P. M., Forest, C. E., & Keller, K. (2017). Deep Uncertainties in Sea-Level Rise and Storm Surge Projections: Implications for Coastal Flood Risk Management. *Risk Analysis*. doi: 10.1111/risa.12888
- Pianosi, F., Beven, K., Freer, J., Hall, J. W., Rougier, J., Stephenson, D. B., & Wagener, T. (2016). Sensitivity analysis of environmental models: A systematic review with practical workflow. *Environmental Modelling & Software*, *79*, 214-232. doi: <http://dx.doi.org/10.1016/j.envsoft.2016.02.008>
- Pruyt, E., & Kwakkel, J. H. (2014). Radicalization under deep uncertainty: a multi-model exploration of activism, extremism, and terrorism. *System Dynamics Review*, *30*(1-2), 1-28.
- Quinn, J. D. (2017). *Characterizing and managing deeply uncertain risks in coupled human-natural systems*. (Ph.D. thesis), Cornell University, New York.
- Quinn, J. D., Reed, P. M., Giuliani, M., & Castelletti, A. (2017). Rival framings: A framework for discovering how problem formulation uncertainties shape risk management trade-offs in water resources systems. *Water Resources Research*, *53*(8), 7208-7233.
- Quinn, J. D., Reed, P. M., Giuliani, M., Castelletti, A., Oyler, J. W., & Nicholas, R. E. (2018). Exploring How Changing Monsoonal Dynamics and Human Pressures Challenge Multi-reservoir Management for Flood Protection, Hydropower Production, and Agricultural Water Supply. *Water Resources Research*, *54*(7), 4638-4662.
- Raso, L., Kwakkel, J., Timmermans, J., & Panthou, G. (2019). How to evaluate a monitoring system for adaptive policies: criteria for signposts selection and their model-based evaluation. *Climatic Change*. doi: 10.1007/s10584-018-2355-3
- Reed, P. M., Hadka, D., Herman, J. D., Kasprzyk, J. R., & Kollat, J. B. (2013). Evolutionary multiobjective optimization in water resources: The past, present, and future. *Advances in Water Resources*, *51*, 438-456. doi: <https://doi.org/10.1016/j.advwatres.2012.01.005>
- Reed, P. M., & Kollat, J. B. (2013). Visual analytics clarify the scalability and effectiveness of massively parallel many-objective optimization: A groundwater monitoring design example. *Adv. Water Resour.*, *56*, 1.
- Reed, P. M., Kollat, J. B., Ferringer, M. P., & Thompson, T. G. (2008). Parallel Evolutionary Multi-Objective Optimization on Large, Heterogeneous Clusters: An Applications Perspective. *Journal of Aerospace Computing, Information, and Communication*, *5*(11), 460-478. doi: 10.2514/1.36467
- Reichert, P., Schuwirth, N., & Langhans, S. (2013). Constructing, evaluating and visualizing value and utility functions for decision support. *Environmental Modelling & Software*, *46*, 283-291. doi: <https://doi.org/10.1016/j.envsoft.2013.01.017>
- Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., . . . Tavoni, M. (2017). The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change*, *42*, 153-168. doi: <https://doi.org/10.1016/j.gloenvcha.2016.05.009>
- Rozenberg, J., Guivarch, C., Lempert, R., & Hallegatte, S. (2014). Building SSPs for climate policy analysis: a scenario elicitation methodology to map the space of possible future challenges to mitigation and adaptation. *Climatic Change*, *122*(3), 509-522. doi: 10.1007/s10584-013-0904-3

- Saltelli, A., Aleksankina, K., Becker, W., Fennell, P., Ferretti, F., Holst, N., . . . Wu, Q. (2019). Why so many published sensitivity analyses are false: A systematic review of sensitivity analysis practices. *Environmental Modelling & Software*, *114*, 29-39. doi: <https://doi.org/10.1016/j.envsoft.2019.01.012>
- Shortridge, J. E., & Zaitchik, B. F. (2018). Characterizing climate change risks by linking robust decision frameworks and uncertain probabilistic projections. *Climatic Change*, *151*(3), 525-539. doi: 10.1007/s10584-018-2324-x
- Singh, R., Reed, P. M., & Keller, K. (2015). Many-objective robust decision making for managing an ecosystem with a deeply uncertain threshold response. *Ecology and Society*, *20*(3), 12.
- Smajgl, A., & Ward, J. (2015). Evaluating participatory research: framework, methods and implementation results. *Journal of Environmental Management*, *157*, 311-319.
- Small, M. J., & Xian, S. (2018). A human-environmental network model for assessing coastal mitigation decisions informed by imperfect climate studies. *Global Environmental Change*, *53*, 137-145. doi: <https://doi.org/10.1016/j.gloenvcha.2018.09.006>
- Song, X., Bryan, B. A., Almeida, A. C., Paul, K. I., Zhao, G., & Ren, Y. (2013). Time-dependent sensitivity of a process-based ecological model. *Ecological Modelling*, *265*, 114-123. doi: <https://doi.org/10.1016/j.ecolmodel.2013.06.013>
- Song, X., Bryan, B. A., Paul, K. I., & Zhao, G. (2012). Variance-based sensitivity analysis of a forest growth model. *Ecological Modelling*, *247*, 135-143. doi: <https://doi.org/10.1016/j.ecolmodel.2012.08.005>
- Srifer, R. L., Lempert, R. J., Wikman-Svahn, P., & Keller, K. (2018). Characterizing uncertain sea-level rise projections to support investment decisions. *PloS One*, *13*(2), e0190641. doi: 10.1371/journal.pone.0190641
- Sterman, J. (2000). *Business dynamics: systems thinking and modeling for a complex world*. USA: Irwin-McGraw-Hill.
- Stewart, I. (1989). *Does God Play Dice: The New Mathematics of Chaos*: Blackwell Publishing, Hoboken, New Jersey, USA.
- Taner, M. Ü., Ray, P., & Brown, C. (2019). Incorporating Multidimensional Probabilistic Information Into Robustness-Based Water Systems Planning. *Water Resources Research*, *55*(5), 3659-3679. doi: 10.1029/2018WR022909
- Tress, G., Tress, B., & Fry, G. (2005). Clarifying Integrative Research Concepts in Landscape Ecology. *Landscape Ecology*, *20*(4), 479-493. doi: 10.1007/s10980-004-3290-4
- Trindade, B., Reed, P., Herman, J., Zeff, H., & Characklis, G. (2017). Reducing regional drought vulnerabilities and multi-city robustness conflicts using many-objective optimization under deep uncertainty. *Advances in Water Resources*, *104*, 195-209.
- Trindade, B. C., Gold, D. F., Reed, P. M., Zeff, H. B., & Characklis, G. W. (2020). Water pathways: An open source stochastic simulation system for integrated water supply portfolio management and infrastructure investment planning. *Environmental Modelling & Software*, *132*, 104772. doi: <https://doi.org/10.1016/j.envsoft.2020.104772>
- Trindade, B. C., Reed, P. M., & Characklis, G. W. (2019). Deeply uncertain pathways: Integrated multi-city regional water supply infrastructure investment and portfolio management. *Advances in Water Resources*, *134*, 103442. doi: <https://doi.org/10.1016/j.advwatres.2019.103442>
- Trutnevyte, E., Guivarch, C., Lempert, R., & Strachan, N. (2016). Reinvigorating the scenario technique to expand uncertainty consideration. *Climatic Change*, *135*(3), 373-379. doi: 10.1007/s10584-015-1585-x
- Tsoukiàs, A. (2008). From decision theory to decision aiding methodology. *European Journal of Operational Research*, *187*(1), 138-161. doi: <https://doi.org/10.1016/j.ejor.2007.02.039>
- UN. (2015). *Transforming our world: the 2030 Agenda for Sustainable Development*. Resolution adopted by the General Assembly on 25 September 2015. The United Nations (UN). Retrieved from https://www.un.org/ga/search/view_doc.asp?symbol=A/RES/70/1&Lang=E
- UN. (2019). *Global Environment Outlook 6*. UN Environment. The Fourth United Nations Environmental Assembly. Retrieved from <https://www.unenvironment.org/resources/global-environment-outlook-6>
- van Bruggen, A., Nikolic, I., & Kwakkel, J. (2019). Modeling with Stakeholders for Transformative Change. *Sustainability*, *11*(3), 825. doi: <https://doi.org/10.3390/su11030825>
- Verburg, P. H., Dearing, J. A., Dyke, J. G., Leeuw, S. v. d., Seitzinger, S., Steffen, W., & Syvitski, J. (2016). Methods and approaches to modelling the Anthropocene. *Global Environmental Change*, *39*, 328-340. doi: <https://doi.org/10.1016/j.gloenvcha.2015.08.007>
- Voinov, A. (2017). Participatory Modeling for Sustainability. In M. A. Abraham (Ed.), *Encyclopedia of Sustainable Technologies* (pp. 33-39). Oxford: Elsevier.

- Voinov, A., Jenni, K., Gray, S., Kolagani, N., Glynn, P. D., Bommel, P., . . . Smajgl, A. (2018). Tools and methods in participatory modeling: Selecting the right tool for the job. *Environmental Modelling & Software*, *109*, 232-255. doi: <https://doi.org/10.1016/j.envsoft.2018.08.028>
- Walker, W., Marchau, V., Bloemen, P., Lawrence, J., Lempert, R., & Kwakkel, J. (2018). Comment on “From Data to Decisions: Processing Information, Biases, and Beliefs for Improved Management of Natural Resources and Environments” by Glynn et al. *Earth's Future*, *6*(5), 757-761. doi: 10.1002/2017EF000750
- Walker, W. E. (2000). Policy analysis: a systematic approach to supporting policymaking in the public sector. *J. Multicriteria Decis. Analysis*, *9*(1-3), 11-27.
- Walker, W. E., Harremoës, P., Rotmans, J., van der Sluijs, J. P., van Asselt, M. B., Janssen, P., & Krayer von Krauss, M. P. (2003). Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support. *Integrated assessment*, *4*(1), 5-17.
- Watson, A. A., & Kasprzyk, J. R. (2017). Incorporating deeply uncertain factors into the many objective search process. *Environmental Modelling & Software*, *89*, 159-171. doi: <http://dx.doi.org/10.1016/j.envsoft.2016.12.001>
- Weaver, C. P., Lempert, R. J., Brown, C., Hall, J. A., Revell, D., & Sarewitz, D. (2013). Improving the contribution of climate model information to decision making: the value and demands of robust decision frameworks. *Wiley Interdisciplinary Reviews: Climate Change*, *4*(1), 39-60.
- Whateley, S., Steinschneider, S., & Brown, C. (2014). A climate change range-based method for estimating robustness for water resources supply. *Water Resour. Res.*, *50*, 8944.
- Wise, R. M., Fazey, I., Stafford Smith, M., Park, S. E., Eakin, H. C., Archer Van Garderen, E. R. M., & Campbell, B. (2014). Reconceptualising adaptation to climate change as part of pathways of change and response. *Global Environmental Change*, *28*, 325-336. doi: <https://doi.org/10.1016/j.gloenvcha.2013.12.002>
- Woodruff, M. J., Reed, P. M., & Simpson, T. W. (2013). Many objective visual analytics: rethinking the design of complex engineered systems. *Structural and Multidisciplinary Optimization*, *48*(1), 201-219. doi: 10.1007/s00158-013-0891-z
- Zare, F., Elsawah, S., Bagheri, A., Nabavi, E., & Jakeman, A. J. (2019). Improved integrated water resource modelling by combining DPSIR and system dynamics conceptual modelling techniques. *Journal of Environmental Management*, *246*, 27-41.
- Zare, F., Guillaume, J. H. A., Jakeman, A. J., & Torabi, O. (2020). Reflective communication to improve problem-solving pathways: Key issues illustrated for an integrated environmental modelling case study. *Environmental Modelling & Software*, *126*, 104645. doi: <https://doi.org/10.1016/j.envsoft.2020.104645>
- Zeff, H. B., Herman, J. D., Reed, P. M., & Characklis, G. W. (2016). Cooperative drought adaptation: Integrating infrastructure development, conservation, and water transfers into adaptive policy pathways. *Water Resources Research*, *52*(9), 7327-7346. doi: 10.1002/2016WR018771
- Zeff, H. B., Kasprzyk, J. R., Herman, J. D., Reed, P. M., & Characklis, G. W. (2014). Navigating financial and supply reliability tradeoffs in regional drought management portfolios. *Water Resources Research*, *50*(6), 4906-4923.
- Zhao, G., Bryan, B. A., King, D., Luo, Z., Wang, E., Bende-Michl, U., . . . Yu, Q. (2013). Large-scale, high-resolution agricultural systems modeling using a hybrid approach combining grid computing and parallel processing. *Environmental Modelling & Software*, *41*, 231-238. doi: <https://doi.org/10.1016/j.envsoft.2012.08.007>
- Zhao, G., Bryan, B. A., & Song, X. (2014). Sensitivity and uncertainty analysis of the APSIM-wheat model: Interactions between cultivar, environmental, and management parameters. *Ecological Modelling*, *279*, 1-11. doi: <https://doi.org/10.1016/j.ecolmodel.2014.02.003>

1 **Appendix A**

2 A note on terminology: The literature uses various—sometimes inconsistent—terms to
3 refer to exploratory modeling practices. The terminology we adopt in this article uses the terms:
4 *approach* for referring to a philosophical position to modeling providing context and logics (e.g.,
5 consolidative modeling vs. exploratory modeling approaches in Bankes (1993));
6 *method/technique/algorithm* for a structured set of processes that can be used for a particular
7 purpose in exploratory modeling (e.g., PRIM or CART in scenario discovery (Lempert *et al.*,
8 2008)); *framework* for a mix of methods that interact to support decision-making (e.g., Robust
9 Decision Making (Lempert, 2019)); *toolkit (tool)* for well-defined and documented resources
10 (e.g., programming libraries) that are external to users and can support the exploratory modeling
11 process (e.g., the Exploratory Modeling Workbench (Kwakkel, 2017) and Rhodium (Hadka *et*
12 *al.*, 2015)).

13 What we are discussing in this article as optimization is the *simulation-based*
14 optimization (Amaran *et al.*, 2016) which is connected to Monte Carlo simulation, reliability
15 engineering, and evolutionary optimization (Beyer & Sendhoff, 2007; Maier *et al.*, 2014;
16 Nicklow *et al.*, 2010; Reed *et al.*, 2013). This class of optimization has been used widely in the
17 deep uncertainty literature for policy search (Gold *et al.*, 2019; Herman *et al.*, 2015; Quinn *et al.*,
18 2017; Trindade *et al.*, 2017). Here we do not discuss stochastic dynamic programming that has
19 been used for policy design through optimizing the sequence and timing of decision variables to
20 trigger adaptation (Fletcher *et al.*, 2019). We also do not discuss earlier works that go back to
21 robust linear programming of the 1980s in operations research (Ben-Tal & Nemirovski, 1998;
22 Ben-Tal & Nemirovski, 1999).

23
24

25 **Appendix B**

26 Exploratory modeling can overlap with other areas that also use model-based
 27 experimentation to analyze the implications of conflicting objectives and alternative
 28 assumptions, such as multi-objective optimization (Reed *et al.*, 2013), design of experiments
 29 (Montgomery, 2017), and sensitivity analysis (Borgonovo & Plischke, 2016; Saltelli *et al.*, 2008;
 30 Saltelli *et al.*, 2000). Therefore, a range of existing methods from other areas can be re-
 31 appropriated to support exploratory modeling for new exploratory purposes.

32 As an example, exploratory modeling overlaps with, and can use methods from,
 33 sensitivity analysis (Giuliani *et al.*, 2014; Kasprzyk *et al.*, 2013; Lamontagne *et al.*, 2018;
 34 Moallemi *et al.*, 2018c; Reed & Kollat, 2013; Singh *et al.*, 2015). Sensitivity analysis, in general,
 35 can be performed in four settings (Jaxa-Rozen & Kwakkel, 2018; Saltelli *et al.*, 2008):

- 36 • *Factor prioritization* to specify important model inputs contributing to output
 37 uncertainties (Loucks *et al.*, 2005);
- 38 • *Factor fixing* to determine the model inputs with the least influence on output
 39 uncertainties (Saltelli *et al.*, 2008);
- 40 • *Variance cutting* to search for input values under which output uncertainty remain below
 41 a threshold (Saltelli & Tarantola, 2002); and
- 42 • *Factor mapping* to identify areas of input uncertainty responsible for a given output (also
 43 related to scenario discovery) (Guivarch *et al.*, 2016; Lamontagne *et al.*, 2018).

44 The sensitivity analysis literature often uses methods in these four settings for different
 45 purposes: to enhance model structure (Iman *et al.*, 2005) in a *consolidative* paradigm by
 46 discarding non-influential inputs (Felli & Hazen, 2004); to inform model calibration and further
 47 data collection (Saltelli *et al.*, 2000); and to identify the direction of change in the behavior of
 48 model outputs (Anderson *et al.*, 2014). In contrast, exploratory modeling adopts sensitivity
 49 analysis for different purposes. For example, it uses similar methods (e.g., factor mapping) for
 50 identifying scenario assumptions that can lead to policy relevant outcomes of interest
 51 (Lamontagne *et al.*, 2018). Exploratory modeling also uses sensitivity analysis methods for
 52 *stress-testing* to identify unexpected model behavior in outcome space (e.g., adaptation tipping
 53 points) and generating a hypothesis about it (Hall *et al.*, 2019). Sensitivity analysis methods can
 54 be also used in an exploratory setting for scenario decomposition to generate a small number of
 55 scenarios as model response to extreme variations of inputs (e.g., worst-case, best-case scenario
 56 discovery) (Tietje, 2005). While the difference between exploratory modeling and other areas is
 57 sometimes just one of disciplinary terminology or purpose, there are also more fundamental
 58 differences related to the treatment of uncertainty. For example, standard uncertainty analysis
 59 tends to rely on well-characterized uncertainties where the joint or marginal probability
 60 distribution of input parameters is known, for example estimated by statistical techniques (e.g.,
 61 histograms) or expert judgement (Loucks *et al.*, 2005). In contrast, exploratory modeling uses
 62 probability distributions *a posteriori* to summarize and describe experiments generated based on
 63 quasi-random samples from the assumption space.

64

65

66 **Appendix C**

67 C.1 Selecting papers for representing the taxonomy

68 Exploratory modeling has been used in a variety of methodological (improvement) work
 69 with illustrative case applications (Kwakkel & Cunningham, 2016; Kwakkel & Jaxa-Rozen,
 70 2016; Rozenberg *et al.*, 2014) as well as in real-world case studies for informing planning and
 71 decision-making (Kwakkel, 2010; Lempert *et al.*, 2013; Lempert *et al.*, 2016). The (illustrative
 72 and real-world) case applications have been across different sectoral domains, including energy
 73 (Auping *et al.*, 2016; Eker & van Daalen, 2015; Moallemi *et al.*, 2017a), climate change
 74 mitigation (Enserink *et al.*, 2013; Greeven *et al.*, 2016; Guivarch *et al.*, 2016; Lempert *et al.*,
 75 1996; Rozenberg *et al.*, 2014), transportation planning (Halim *et al.*, 2016; Kwakkel *et al.*,
 76 2010), flood risk management (Kwakkel *et al.*, 2016; Lempert *et al.*, 2013), water resource
 77 management (de Haan *et al.*, 2016; Huskova *et al.*, 2016; Matrosov *et al.*, 2013), defense
 78 planning (Brooks *et al.*, 1999; Lempert *et al.*, 2016; Moallemi *et al.*, 2018a; Moallemi *et al.*,
 79 2018b; Niese & Singer, 2014), and health management and disease prevention (Auping *et al.*,
 80 2017; Manheim *et al.*, 2016). From these many previous studies, in Section 3 of the manuscript,
 81 we only used some to demonstrate our proposed taxonomy in practice and to represent the
 82 diversity of the field across different types of exploratory modeling (but not covering all previous
 83 work as we were not undertaking a review). For example, there are many studies that use
 84 exploratory modeling for stress-testing, some of which cited in Table 1. We tried to cover
 85 examples of stress-testing across different sectoral domain (e.g., water and energy) and with
 86 different methodological innovations (e.g., stress-testing with sensitivity analysis versus stress-
 87 testing with many-objective optimization). In selecting the articles, we focused on diversity
 88 rather than coverage as we aimed to inform modelers about a variety of the ways that exploratory
 89 modeling has been used in the past and can be also used in the future.

90 The way we selected the articles was guided by the authors' informed judgement from
 91 the recent literature in the three following steps:

- 92 1. We firstly solicited an initial list of representative articles that could exemplify different
 93 types of exploratory modeling in our taxonomy. We identified this initial list by looking at
 94 the modeling papers in the Decision-Making Under Deep Uncertainty (DMDU) literature
 95 (Marchau *et al.*, 2019), as it was the main and closest research community to exploratory
 96 modeling in decision support.
- 97 2. We discuss the initial list within the author team to add new papers to the list based on the
 98 less represented areas of the literature. In improving the initial list, we decided to include
 99 the studies where original data and new decision insights are created (rather than
 100 conceptual discussion), the focus is on a method improvement and/or a new application
 101 (rather than a review), and the context of the study is human and natural systems. Given
 102 these selection criteria, we did not to include the original introductory studies that
 103 discussed the foundations and concepts (Bankes, 2002a, 2002b; Bankes *et al.*, 2001;
 104 Brown *et al.*, 2012). We did not include the review studies as their primary aim was to
 105 provide an overarching overview of the field rather than generating decision insights for a
 106 specific application (Giuliani & Castelletti, 2016; Guivarch *et al.*, 2017; Herman *et al.*,
 107 2020; Herman *et al.*, 2015; Kwakkel & Haasnoot, 2019; Reed *et al.*, 2013; Trutnevyte *et*
 108 *al.*, 2016). We excluded examples from other areas rather than human-natural systems
 109 (e.g., engineering systems and defense planning) as they were not aligned with the

110 article's aim and the journal's scope. We also did not consider articles from the broader
111 areas of sensitivity analysis and optimization (Bryan & Crossman, 2013; Jaxa-Rozen &
112 Kwakkel, 2018; Pianosi *et al.*, 2016; Pye *et al.*, 2015) as they were of the secondary
113 importance for the specific purpose of the current article.

114 3. We reviewed each paper in the list to specify its position in Table 1 with respect to type of
115 exploratory modeling, context, and application. We cross-checked the results within the
116 author team to make sure about the correct understanding of the position of the papers in
117 the table. We also acknowledged that the position of the selected studies in the table is
118 based on the authors' judgement and according to the proposed taxonomy.

119 C.2 Examples from exploratory modeling applications

120 This rest of this appendix briefly summarizes three examples from the variety of
121 exploratory modeling applications: long-term policy analysis of energy systems, future adaptive
122 planning for flood risk management, and theory testing of water systems management from a
123 historic perspective. We choose these three examples as they represent some of the diversity of
124 exploratory modeling applications discussed in Section 3.

125 Example I – Policy analysis in energy transitions modeling

126 The first example combines a methodological work with a real-world case application in
127 energy sector and is from Moallemi *et al.* (2017a). The study is about how qualitative narratives
128 of sustainability transitions can support the computational process of exploratory modeling in
129 long-term policy analysis. The study also analyses future transition pathways towards renewable
130 electricity in India for meeting 100 GW solar electricity and 60 GW wind electricity in a period
131 from 1990 to 2030. This transition unfolds in a context where multiple techno-economic
132 uncertainties (e.g., fuel prices) and socio-political uncertainties (such as electricity demand)
133 challenge a robust understanding of possible future pathways. Therefore, it is important to
134 understand how future transition pathways pan out (i.e. whether the renewable targets will be
135 met or not) and what conditions can redirect this transition towards the targets.

136 The study initially develops qualitative narratives, developed based on the interpretation
137 of raw data from available documents through the lens of sustainability transitions theories
138 (Moallemi *et al.*, 2017b). These narratives differentiate among different structure of the
139 electricity sector (whether it would be dominated by market or government control) and the
140 priorities for the electricity sector (e.g., energy equity, energy security, and sustainability) and
141 use them to guide the development of some deliberate assumption spaces of future in which
142 transition could unfold. Computational experiments are performed within each deliberate
143 assumption space—each experiment corresponds to a single transition pathway. Many transition
144 pathways are analyzed across assumption spaces to assess the fulfilment of wind and solar
145 targets across different pathways.

146 The analysis of experiments using scenario discovery (Bryant & Lempert, 2010) and
147 multi-dimensional clustering (Gerst *et al.*, 2013) shows that the realization of the 100 GW solar
148 electricity by 2022 is unlikely while it is most likely around 2028. However, meeting the 60 GW
149 target for wind electricity by 2022 is closer to reality as the most-likely time for the fulfilment of
150 this target is around 2024. The analysis also shows that a transition pathway towards a
151 renewable—mainly solar—electricity is more likely under conditions when the structure for the

152 electricity sector is government controlled through systemic coordination of renewable initiatives
153 and when energy security and sustainability are dual priorities.

154 Example II – Adaptive planning in flood risk management

155 The second example combines methodological work with an illustrative application in
156 flood risk management and is from Kwakkel *et al.* (2015). The study is about how many-
157 objective robust optimization can computationally support the design of adaptive plans within
158 the Dynamic Adaptive Policy Pathways framework (Haasnoot *et al.*, 2013). There are two
159 challenges with the original design of this framework: how to choose a sequence of actions—
160 known as pathways which remain valid under transient scenarios? and how to cope with the
161 combinatorial problem which arises from the multiplicity of ways which actions can be
162 concatenated? This computational support is intended to help in identifying the most promising
163 pathways with respect to multiple objectives using many-objective optimization and assessing
164 the robustness of pathways over many scenarios by sampling over uncertainty space. The study
165 uses a hypothetical case in Rhine Delta in the Netherlands over the next 100 years. The flood risk
166 management in this case is surrounded by uncertain factors, such as socio-economic
167 development factors (e.g., population and economic growth), global climate change (e.g.,
168 droughts and increase in temperature), and land use (e.g., de-urbanization or fast urbanization).

169 The design of adaptive plan starts initially by identifying policy actions, such as flood
170 prevention measures, heightening the dikes, and strengthening the dikes, for meeting objectives
171 regarding costs, causalities, and damages. Many adaptation pathways can be constructed based
172 on different concatenation of these policy actions and by considering possible various transfers
173 between actions at actions' sell-by dates. The study formulates a many-objective optimization
174 problem and uses optimization (metaheuristic) evolutionary algorithms to enumerate different
175 concatenation of these policy actions—in the form of policy pathways—which minimize the
176 costs, causalities, and damages under two constraints of limiting maximum damages and
177 maximum causalities. The study generates transient scenarios by sampling from uncertainty
178 space and then runs computational experiments to test the robustness of enumerated pathways
179 over generated scenarios. The final result is an adaptation map representing different sequences
180 of actions (pathways) with their respective sell-by dates leading to specific futures. Decision
181 makers could decide which sequence of actions to choose based on their preference or a cost-
182 benefit analysis.

183 Example III – Theory testing in urban water management

184 The third example combines methodological innovation with a real-world case
185 application and is from de Haan *et al.* (2016). The study is an application of exploratory
186 modeling to theory testing (non-decision support) on a historical case, which is a less
187 investigated use of exploratory modeling in the literature. The exploratory model—called STM
188 (Societal Transitions Module)—generates scenarios of transition pathways, more precisely put:
189 the uptake and phasing out of servicing solutions (types of technology) in urban water systems.
190 STM implements a theory of change known as the Multi-Pattern Approach by de Haan and
191 Rotmans (2011) and, perhaps atypically, the model exploits the acknowledged uncertainties in
192 this theory, rather than in estimated parameter values. The theory states that, given certain
193 conditions, at any point in time, one of *several* patterns of change may follow—the theory is
194 agnostic as to which pattern is more likely.

195 Exploratory modeling for STM amounts to producing a portfolio of scenarios starting
 196 from one initial condition. For example, 50 time steps with six patterns possible at each time step
 197 would yield about 6^{50} scenarios. This produces two problems: (1) this is computationally
 198 infeasible, and (2) what should be the interpretation of such a multitude of possibilities? Can
 199 these scenarios give any meaningful information about pathways at all? The former issue is
 200 easily solved by sampling the solution space, limiting the runs to, e.g., 2000-5000 scenarios. The
 201 latter issue is addressed by performing a cluster analysis on the produced scenarios. It turns out
 202 that although each scenario is different, many are very much alike and the thousands of possible
 203 outcomes can be grouped into a handful of clusters. This is the idea behind the title of this study
 204 ‘Many Roads to Rome’, there are many scenarios that, though different in detail, lead to
 205 qualitatively similar outcomes.

206 The STM is set up to re-produce a known historical trajectory of green infrastructure
 207 uptake in Melbourne’s urban water management system from 1960-2010. Though STM produces
 208 several clusters of pathways, one matches the historical data well. The other clusters can be
 209 interpreted as alternative histories, developments that could have been.

210

211 Appendix references

- 212 Amaran, S., Sahinidis, N. V., Sharda, B., & Bury, S. J. (2016). Simulation optimization: a review of algorithms and
 213 applications. *Annals of Operations Research*, 240(1), 351-380.
- 214 Anderson, B., Borgonovo, E., Galeotti, M., & Roson, R. (2014). Uncertainty in climate change modeling: can global
 215 sensitivity analysis be of help? *Risk Analysis*, 34(2), 271-293.
- 216 Auping, W., Pruyt, E., & Kwakkel, J. (2017). Simulating endogenous dynamics of intervention-capacity
 217 deployment: Ebola outbreak in Liberia. *International Journal of Systems Science: Operations & Logistics*,
 218 4(1), 53-67. doi: 10.1080/23302674.2015.1128576
- 219 Auping, W. L., Pruyt, E., de Jong, S., & Kwakkel, J. H. (2016). The geopolitical impact of the shale revolution:
 220 Exploring consequences on energy prices and rentier states. *Energy Policy*, 98, 390-399.
- 221 Bankes, S. (1993). Exploratory modeling for policy analysis. *Operations Research*, 41(3), 435-449.
- 222 Bankes, S. C. (2002a). Agent-based modeling: A revolution? *Proceedings of the National Academy of Sciences*,
 223 99(suppl 3), 7199-7200. doi: 10.1073/pnas.072081299
- 224 Bankes, S. C. (2002b). Tools and techniques for developing policies for complex and uncertain systems.
 225 *Proceedings of the National Academy of Sciences*, 99(suppl 3), 7263-7266. doi: 10.1073/pnas.092081399
- 226 Bankes, S. C., Lempert, R. J., & Popper, S. W. (2001). Computer-assisted reasoning. *Computing in Science &*
 227 *Engineering*, 3(2), 71-77. doi: 10.1109/5992.909006
- 228 Ben-Tal, A., & Nemirovski, A. (1998). Robust convex optimization. *Math. Oper. Res.*, 23, 769.
- 229 Ben-Tal, A., & Nemirovski, A. (1999). Robust solutions of uncertain linear programs. *Operations research letters*,
 230 25(1), 1-13.
- 231 Beyer, H.-G., & Sendhoff, B. (2007). Robust optimization—a comprehensive survey. *Computer methods in applied*
 232 *mechanics engineering*, 196(33-34), 3190-3218.
- 233 Borgonovo, E., & Plischke, E. (2016). Sensitivity analysis: A review of recent advances. *European Journal of*
 234 *Operational Research*, 248(3), 869-887. doi: <https://doi.org/10.1016/j.ejor.2015.06.032>
- 235 Brooks, A., Bankes, S., & Bennett, B. (1999). An application of exploratory analysis: the weapon mix problem.
 236 *Military Operations Research*, 4(1), 67-80.
- 237 Brown, C., Ghile, Y., Laverty, M., & Li, K. (2012). Decision Scaling: Linking bottom-up vulnerability analysis with
 238 climate projections in the water sector. *Water Resources Research*, 48(9).
- 239 Bryan, B. A., & Crossman, N. D. (2013). Impact of multiple interacting financial incentives on land use change and
 240 the supply of ecosystem services. *Ecosystem Services*, 4, 60-72. doi:
 241 <https://doi.org/10.1016/j.ecoser.2013.03.004>
- 242 Bryant, B. P., & Lempert, R. J. (2010). Thinking inside the box: A participatory, computer-assisted approach to
 243 scenario discovery. *Technological Forecasting and Social Change*, 77(1), 34-49.

- 244 de Haan, F., & Rotmans, J. (2011). Patterns in transitions: Understanding complex chains of change. *Technological*
 245 *Forecasting and Social Change*, 78(1), 90-102.
- 246 de Haan, F. J., Rogers, B. C., Brown, R. R., & Deletic, A. (2016). Many roads to Rome: The emergence of pathways
 247 from patterns of change through exploratory modelling of sustainability transitions. *Environmental*
 248 *Modelling & Software*, 85, 279-292. doi: <http://dx.doi.org/10.1016/j.envsoft.2016.05.019>
- 249 Eker, S., & van Daalen, E. (2015). A model-based analysis of biomethane production in the Netherlands and the
 250 effectiveness of the subsidization policy under uncertainty. *Energy Policy*, 82, 178-196. doi:
 251 <http://dx.doi.org/10.1016/j.enpol.2015.03.019>
- 252 Enserink, B., Kwakkel, J. H., & Veenman, S. (2013). Coping with uncertainty in climate policy making:
 253 (Mis)understanding scenario studies. *Futures*, 53, 1-12. doi: <https://doi.org/10.1016/j.futures.2013.09.006>
- 254 Felli, J. C., & Hazen, G. B. (2004). Javelin diagrams: A graphical tool for probabilistic sensitivity analysis. *Decision*
 255 *Analysis*, 1(2), 93-107.
- 256 Fletcher, S., Lickley, M., & Strzepek, K. (2019). Learning about climate change uncertainty enables flexible water
 257 infrastructure planning. *Nature Communications*, 10(1), 1782. doi: 10.1038/s41467-019-09677-x
- 258 Gerst, M. D., Wang, P., & Borsuk, M. E. (2013). Discovering plausible energy and economic futures under global
 259 change using multidimensional scenario discovery. *Environmental Modelling & Software*, 44, 76-86. doi:
 260 <http://dx.doi.org/10.1016/j.envsoft.2012.09.001>
- 261 Giuliani, M., & Castelletti, A. (2016). Is robustness really robust? How different definitions of robustness impact
 262 decision-making under climate change. *Climatic Change*, 135(3), 409-424. doi: 10.1007/s10584-015-1586-
 263 9
- 264 Giuliani, M., Herman, J. D., Castelletti, A., & Reed, P. (2014). Many-objective reservoir policy identification and
 265 refinement to reduce policy inertia and myopia in water management. *Water Resources Research*, 50(4),
 266 3355-3377. doi: 10.1002/2013WR014700
- 267 Gold, D. F., Reed, P. M., Trindade, B. C., & Characklis, G. W. (2019). Identifying Actionable Compromises:
 268 Navigating Multi-City Robustness Conflicts to Discover Cooperative Safe Operating Spaces for
 269 Regional Water Supply Portfolios. *Water Resources Research*, n/a(n/a). doi: 10.1029/2019WR025462
- 270 Greeven, S., Kraan, O., Chappin, Eacute, mile, J. L., & Kwakkel, J. H. (2016). The Emergence of Climate Change
 271 Mitigation Action by Society: An Agent-Based Scenario Discovery Study. *Journal of Artificial Societies*
 272 *and Social Simulation*, 19(3), 9. doi: <http://dx.doi.org/10.18564/jasss.3134>
- 273 Guivarch, C., Lempert, R., & Trutnevyte, E. (2017). Scenario techniques for energy and environmental research: An
 274 overview of recent developments to broaden the capacity to deal with complexity and uncertainty.
 275 *Environmental Modelling & Software*, 97, 201-210. doi: <http://dx.doi.org/10.1016/j.envsoft.2017.07.017>
- 276 Guivarch, C., Rozenberg, J., & Schweizer, V. (2016). The diversity of socio-economic pathways and CO2 emissions
 277 scenarios: Insights from the investigation of a scenarios database. *Environmental Modelling & Software*,
 278 80, 336-353. doi: <http://dx.doi.org/10.1016/j.envsoft.2016.03.006>
- 279 Haasnoot, M., Kwakkel, J. H., Walker, W. E., & ter Maat, J. (2013). Dynamic adaptive policy pathways: A method
 280 for crafting robust decisions for a deeply uncertain world. *Global Environmental Change*, 23(2), 485-498.
 281 doi: <http://dx.doi.org/10.1016/j.gloenvcha.2012.12.006>
- 282 Hadka, D., Herman, J., Reed, P., & Keller, K. (2015). An open source framework for many-objective robust
 283 decision making. *Environmental Modelling & Software*, 74, 114-129. doi:
 284 <https://doi.org/10.1016/j.envsoft.2015.07.014>
- 285 Halim, R. A., Kwakkel, J. H., & Tavasszy, L. A. (2016). A scenario discovery study of the impact of uncertainties in
 286 the global container transport system on European ports. *Futures*, 81, 148-160. doi:
 287 <http://dx.doi.org/10.1016/j.futures.2015.09.004>
- 288 Hall, J. W., Harvey, H., & Manning, L. J. (2019). Adaptation thresholds and pathways for tidal flood risk
 289 management in London. *Climate Risk Management*, 24, 42-58. doi:
 290 <https://doi.org/10.1016/j.crm.2019.04.001>
- 291 Herman, J. D., Quinn, J. D., Steinschneider, S., Giuliani, M., & Fletcher, S. (2020). Climate Adaptation as a Control
 292 Problem: Review and Perspectives on Dynamic Water Resources Planning Under Uncertainty. *Water*
 293 *Resources Research*, 56(2), e24389. doi: 10.1029/2019WR025502
- 294 Herman, J. D., Reed, P. M., Zeff, H. B., & Characklis, G. W. (2015). How should robustness be defined for water
 295 systems planning under change? *Journal of Water Resources Planning and Management*, 141(10),
 296 04015012.
- 297 Huskova, I., Matrosov, E. S., Harou, J. J., Kasprzyk, J. R., & Lambert, C. (2016). Screening robust water
 298 infrastructure investments and their trade-offs under global change: A London example. *Global*
 299 *Environmental Change*, 41, 216-227. doi: <http://dx.doi.org/10.1016/j.gloenvcha.2016.10.007>

- 300 Iman, R. L., Johnson, M. E., & Watson, C. C. (2005). Uncertainty analysis for computer model projections of
301 hurricane losses. *Risk Analysis*, 25(5), 1299-1312.
- 302 Jaxa-Rozen, M., & Kwakkel, J. (2018). Tree-based ensemble methods for sensitivity analysis of environmental
303 models: A performance comparison with Sobol and Morris techniques. *Environmental Modelling &
304 Software*, 107, 245-266. doi: <https://doi.org/10.1016/j.envsoft.2018.06.011>
- 305 Kasprzyk, J. R., Nataraj, S., Reed, P. M., & Lempert, R. J. (2013). Many objective robust decision making for
306 complex environmental systems undergoing change. *Environmental Modelling & Software*, 42, 55-71. doi:
307 <http://dx.doi.org/10.1016/j.envsoft.2012.12.007>
- 308 Kwakkel, J., Haasnoot, M., & Walker, W. (2015). Developing dynamic adaptive policy pathways: A computer-
309 assisted approach for developing adaptive strategies for a deeply uncertain world. *Climatic Change*, 132,
310 373.
- 311 Kwakkel, J. H. (2010). *The treatment of uncertainty in airport strategic planning*. (Ph.D.), Delft University of
312 Technology, The Netherlands.
- 313 Kwakkel, J. H. (2017). The Exploratory Modeling Workbench: An open source toolkit for exploratory modeling,
314 scenario discovery, and (multi-objective) robust decision making. *Environmental Modelling & Software*,
315 96, 239-250. doi: <http://dx.doi.org/10.1016/j.envsoft.2017.06.054>
- 316 Kwakkel, J. H., & Cunningham, S. C. (2016). Improving scenario discovery by bagging random boxes.
317 *Technological Forecasting and Social Change*, 111, 124-134. doi:
318 <http://dx.doi.org/10.1016/j.techfore.2016.06.014>
- 319 Kwakkel, J. H., & Haasnoot, M. (2019). Supporting DMDU: A Taxonomy of Approaches and Tools. In V. A. W. J.
320 Marchau, W. E. Walker, P. Bloemen & S. Popper (Eds.), *Decision Making Under Deep Uncertainty –
321 From Theory to Practice*: Springer.
- 322 Kwakkel, J. H., Haasnoot, M., & Walker, W. E. (2016). Comparing Robust Decision-Making and Dynamic
323 Adaptive Policy Pathways for model-based decision support under deep uncertainty. *Environmental
324 Modelling & Software*, 86, 168-183. doi: <http://dx.doi.org/10.1016/j.envsoft.2016.09.017>
- 325 Kwakkel, J. H., & Jaxa-Rozen, M. (2016). Improving scenario discovery for handling heterogeneous uncertainties
326 and multinomial classified outcomes. *Environmental Modelling & Software*, 79, 311-321. doi:
327 <http://dx.doi.org/10.1016/j.envsoft.2015.11.020>
- 328 Kwakkel, J. H., Walker, W. E., & Marchau, V. A. W. J. (2010). Adaptive airport strategic planning. *European
329 Journal of Transport and Infrastructure Research*, 10, 249–273.
- 330 Lamontagne, J. R., Reed, P. M., Link, R., Calvin, K. V., Clarke, L. E., & Edmonds, J. A. (2018). Large Ensemble
331 Analytic Framework for Consequence-Driven Discovery of Climate Change Scenarios. 6(3), 488-504. doi:
332 doi:10.1002/2017EF000701
- 333 Lempert, R. J. (2019). Robust Decision Making (RDM). In V. Marchau, W. Walker, P. Bloemen & S. Popper (Eds.),
334 *Decision Making under Deep Uncertainty: From Theory to Practice* (pp. 23-51). Cham: Springer
335 International Publishing.
- 336 Lempert, R. J., Bryant, B. P., & Bankes, S. C. (2008). Comparing algorithms for scenario discovery. *RAND, Santa
337 Monica, CA*.
- 338 Lempert, R. J., Kalra, N., Peyraud, S., Mao, Z., Tan, S. B., Cira, D., & Lotsch, A. (2013). *Ensuring Robust Flood
339 Risk Management in Ho Chi Minh City*. Policy Research Working Paper 6465. World Bank.
- 340 Lempert, R. J., Schlesinger, M. E., & Bankes, S. C. (1996). When we don't know the costs or the benefits: Adaptive
341 strategies for abating climate change. *Climatic Change*, 33(2), 235-274. doi: 10.1007/BF00140248
- 342 Lempert, R. J., Warren, D., Henry, R., Button, R., Klenk, J., & Giglio, K. (2016). Defence resource planning under
343 uncertainty. *RAND report*.
- 344 Loucks, D. P., Van Beek, E., Stedinger, J. R., Dijkman, J. P., & Villars, M. T. (2005). *Water resources systems
345 planning and management: an introduction to methods, models and applications*: Paris: Unesco.
- 346 Maier, H. R., Kapelan, Z., Kasprzyk, J., Kollat, J., Matott, L., Cunha, M., . . . Marchi, A. (2014). Evolutionary
347 algorithms and other metaheuristics in water resources: Current status, research challenges and future
348 directions. *Environmental Modelling & Software*, 62, 271-299.
- 349 Manheim, D., Chamberlin, M., Osoba, O. A., Vardavas, R., & Moore, M. (2016). *Improving Decision Support for
350 Infectious Disease Prevention and Control: Aligning Models and Other Tools with Policymakers' Needs*.
351 RAND Corporation. Santa Monica, CA. Retrieved from
352 https://www.rand.org/pubs/research_reports/RR1576.html
- 353 Marchau, V. A. W. J., Walker, W. E., Bloemen, P. J. T. M., & Popper, S. W. (2019). *Decision Making under Deep
354 Uncertainty: From Theory to Practice*. New York: Springer.

- 355 Matrosov, E. S., Woods, A. M., & Harou, J. J. (2013). Robust Decision Making and Info-Gap Decision Theory for
 356 water resource system planning. *Journal of Hydrology*, 494, 43-58. doi:
 357 <http://doi.org/10.1016/j.jhydrol.2013.03.006>
- 358 Moallemi, E. A., de Haan, F., Kwakkel, J., & Aye, L. (2017a). Narrative-informed exploratory analysis of energy
 359 transition pathways: A case study of India's electricity sector. *Energy Policy*, 110, 271–287. doi:
 360 <https://doi.org/10.1016/j.enpol.2017.08.019>
- 361 Moallemi, E. A., de Haan, F. J., Webb, J. M., George, B. A., & Aye, L. (2017b). Transition dynamics in state-
 362 influenced niche empowerments: Experiences from India's electricity sector. *Technological Forecasting &*
 363 *Social Change*, 116, 129–141. doi: <http://dx.doi.org/10.1016/j.techfore.2016.10.067>
- 364 Moallemi, E. A., El Sawah, S., Turan, H. H., & Ryan, M. (2018a). Multi-objective decision making in acquisition
 365 planning under deep uncertainty. In M. Rabe, A. A. Juan, N. Mustafee, A. Skoogh, S. Jain & B. Johansson
 366 (eds), *2018 Winter Simulation Conference (WSC)* (1334-1345), Gothenburg.
- 367 Moallemi, E. A., El Sawah, S., & Ryan, M. (2018b). Model-based multi-objective decision making under deep
 368 uncertainty from a multi-method design lens. *Simulation Modelling Practice & Theory*, 84, 232–250. doi:
 369 <https://doi.org/10.1016/j.simpat.2018.02.009>
- 370 Moallemi, E. A., El Sawah, S., & Ryan, M. J. (2018c). An agent-monitored framework for the output-oriented design
 371 of experiments in exploratory modelling. *Simulation Modelling Practice and Theory*, 89, 48-63. doi:
 372 <https://doi.org/10.1016/j.simpat.2018.09.008>
- 373 Montgomery, D. C. (2017). *Design and analysis of experiments*: John Wiley & Sons.
- 374 Nicklow, J., Reed, P., Savic, D., Dessalegne, T., Harrell, L., Chan-Hilton, A., . . . Singh, A. (2010). State of the art
 375 for genetic algorithms and beyond in water resources planning and management. *Journal of Water*
 376 *Resources Planning and Management*, 136(4), 412-432.
- 377 Niese, N. D., & Singer, D. J. (2014). Assessing changeability under uncertain exogenous disturbance. *Research in*
 378 *Engineering Design*, 25(3), 241-258. doi: 10.1007/s00163-014-0177-5
- 379 Pianosi, F., Beven, K., Freer, J., Hall, J. W., Rougier, J., Stephenson, D. B., & Wagener, T. (2016). Sensitivity
 380 analysis of environmental models: A systematic review with practical workflow. *Environmental Modelling*
 381 *& Software*, 79, 214-232. doi: <http://dx.doi.org/10.1016/j.envsoft.2016.02.008>
- 382 Pye, S., Sabio, N., & Strachan, N. (2015). An integrated systematic analysis of uncertainties in UK energy transition
 383 pathways. *Energy Policy*, 87, 673-684. doi: <http://dx.doi.org/10.1016/j.enpol.2014.12.031>
- 384 Quinn, J. D., Reed, P. M., Giuliani, M., & Castelletti, A. (2017). Rival framings: A framework for discovering how
 385 problem formulation uncertainties shape risk management trade-offs in water resources systems. *Water*
 386 *Resources Research*, 53(8), 7208-7233.
- 387 Reed, P. M., Hadka, D., Herman, J. D., Kasprzyk, J. R., & Kollat, J. B. (2013). Evolutionary multiobjective
 388 optimization in water resources: The past, present, and future. *Advances in Water Resources*, 51, 438-456.
 389 doi: <https://doi.org/10.1016/j.advwatres.2012.01.005>
- 390 Reed, P. M., & Kollat, J. B. (2013). Visual analytics clarify the scalability and effectiveness of massively parallel
 391 many-objective optimization: A groundwater monitoring design example. *Adv. Water Resour.*, 56, 1.
- 392 Rozenberg, J., Guivarch, C., Lempert, R., & Hallegatte, S. (2014). Building SSPs for climate policy analysis: a
 393 scenario elicitation methodology to map the space of possible future challenges to mitigation and
 394 adaptation. *Climatic Change*, 122(3), 509-522. doi: 10.1007/s10584-013-0904-3
- 395 Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., . . . Tarantola, S. (2008). *Global*
 396 *Sensitivity Analysis*. Chichester, England: John Wiley and Sons.
- 397 Saltelli, A., & Tarantola, S. (2002). On the relative importance of input factors in mathematical models: safety
 398 assessment for nuclear waste disposal. *Journal of the American Statistical Association*, 97(459), 702-709.
- 399 Saltelli, A., Tarantola, S., & Campolongo, F. (2000). Sensitivity analysis as an ingredient of modeling. *Statistical*
 400 *Science*, 377-395.
- 401 Singh, R., Reed, P. M., & Keller, K. (2015). Many-objective robust decision making for managing an ecosystem
 402 with a deeply uncertain threshold response. *Ecology and Society*, 20(3), 12.
- 403 Tietje, O. (2005). Identification of a small reliable and efficient set of consistent scenarios. *European Journal of*
 404 *Operational Research*, 162(2), 418-432. doi: <https://doi.org/10.1016/j.ejor.2003.08.054>
- 405 Trindade, B., Reed, P., Herman, J., Zeff, H., & Characklis, G. (2017). Reducing regional drought vulnerabilities and
 406 multi-city robustness conflicts using many-objective optimization under deep uncertainty. *Advances in*
 407 *Water Resources*, 104, 195-209.
- 408 Trutnevyte, E., Guivarch, C., Lempert, R., & Strachan, N. (2016). Reinvigorating the scenario technique to expand
 409 uncertainty consideration. *Climatic Change*, 135(3), 373-379. doi: 10.1007/s10584-015-1585-x

