Climate Risk Management

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Abstract: Accelerating global climate change drives new climate risks. People around the world are researching, designing, and implementing strategies to manage these risks. Identifying and implementing sound climate risk management strategies poses nontrivial challenges including: (i) linking the required disciplines, (ii) identifying relevant values and objectives, (iii) identifying and quantifying important uncertainties, (iv) resolving interactions between decision-levers and the system dynamics, (v) quantifying the trade-offs between diverse values under deep and dynamic uncertainties, (vi) communicating to inform decisions, and (vii) learning from the decision-making needs to inform research design. Here we review these challenges and avenues to overcome them.

Keywords: Climate Change, Risk Management, Convergence Science, Many Objective Robust Decision Making, Decision Support, Mission-Oriented Basic Science

1. Humans are Changing Climate Risks

Humans have changed the Earth's climate (Field et al., 2014). The burning of fossil fuels has drastically increased the concentration of greenhouse gases in the Earth's atmosphere (Matthews et al., 2014). These greenhouse gas emissions have altered the climate (Alexander et al., 2013; Sippel et al., 2020), with more changes locked in (Levermann et al., 2013; Matthews and Weaver, 2010). Climatic change can increase hazards (Hultman et al., 2010). In many regions, sea levels are rising (Slangen et al., 2016), storm surges and heat waves are intensifying (Donat et al., 2013; Grinsted et al., 2013), and droughts are becoming more frequent (Hoerling et al., 2012).

Natural and human systems are exposed and vulnerable to these changing climate hazards. For example, people live behind levees that can be overtopped when a hurricane strikes (Jonkman et al., 2009), communities rely on ecosystem services from drought-sensitive forests (Lindner et al., 2010), and heatwaves increase human mortality risks (Anderson and Bell, 2011).

Risks occur through interactions between hazards, exposures, and vulnerabilities (see the discussion in Field et al., 2014). A common definition of risk in the climate change literature is: "the potential for consequences where something of value is at stake and where the outcome is uncertain, recognizing the diversity of values. Risk is often represented as probability of occurrence of hazardous events or trends multiplied by the impacts if these events or trends occur." (Oppenheimer et al., 2014). This definition is consistent with alternatives such as the "effect of uncertainty on objectives" (Lark, 2015) or the (ii) "the combination of probability and magnitude/severity of consequences" (Society for Risk Analysis, 2013). Changes in climate hazards, exposures, and vulnerabilities change climate risks (AghaKouchak et al., 2020; Hultman et al., 2010). Climate risk management analyzes and designs strategies to manage these risks (Kunreuther et al., 2013; Travis and Bates, 2014).

This article reviews research to inform decisions on how to manage changing climate risks. We start with an overview of approaches to manage climate risks (section 2). We then discuss why improving climate risk management strategies requires understanding complex coupled systems (section 3). We then turn our attention to research challenges and avenues to overcoming them (section 4) and provide a summary in the conclusions (section 5).

2. Climate Risk Can Be Managed Through Multiple Levers

The individual actions that can be combined to form potential strategies are often referred to as decision levers (Lempert et al., 2003). The "lever" terminology draws an analogy between a technocratic view of a decision problem and a machine which is controlled using a combination of manual inputs. For example, a home-owner facing increased flooding risks has several decision levers at their disposal, including purchasing flood insurance, flood-proofing or elevating their home, abandoning their home, and advocating that their government build risk mitigation structures such as levees. Many of these levers can be used by themselves or in combination with others, forming a range of strategies that the home-owner might use for managing the flood risk. Climate risk-management levers generally fall into four categories: mitigation, adaptation, carbon sequestration, and solar radiation management (Figure 1).

Mitigation consists mostly of reducing the emissions of greenhouse gases into the atmosphere to reduce the intensity of future climate change. Examples of mitigation policies include caps on emissions and subsidies for renewable or more-efficient technologies. Mitigation reduces many future hazards, though these benefits are delayed due to the inertia of the climate system (Ricke and Caldeira, 2014; Tebaldi and Friedlingstein, 2013). The potential climate benefits of mitigation are also subject to large climate- and biogeochemical-system uncertainties (Bodman et al., 2013; Huntingford et al., 2009).

Adaptation involves strategies to reduce the negative impacts of committed or anticipated climatic changes by reducing the associated hazards, exposures and/or vulnerabilities. Examples include changes in forest management, land-use planning, and the design of engineering infrastructures (Field et al., 2014). Here we focus on the example of coastal adaptation to changes in sea levels and storm surges given the large global impact of increased flooding (Hinkel et al., 2014). In this setting, adaptation actions might include changing land-use policy to reduce development and settlement in flood plains, incentivizing flood proofing or house elevation, constructing seawalls, or improving resilience, for example by improving the recovery from flooding events (Schelfaut et al., 2011). (We will return to a discussion of these levers in section 3). While adaptation can be flexible in responding to local circumstances and stakeholder needs, these measures can require a long-term commitment to adaptive strategies given the climate and socioeconomic uncertainties (Haasnoot et al., 2013; Walker et al., 2013).

Carbon sequestration (or carbon dioxide removal) aims to capture and store carbon dioxide (CO_2) from the atmosphere. This may be done actively, through the use of negative emissions technologies (NETs), or passively, through activities such as re- or afforestation (Lal, 2008). Examples of proposed NETs include bioenergy with carbon capture and sequestration (BECCS) (Fridahl and Lehtveer, 2018), and direct air capture of CO_2, or DAC (Chen and Tavoni, 2013; Lackner, 2013). NETs, and in particular BECCS, are commonly used in emissions scenarios reaching the Paris Agreement targets of limiting temperature anomalies to 1.5^{o} or 2^{o}C from pre-industrial (Hilaire et al., 2019). At least one small-scale BECCS project has been announced at a power plant (The Economist, 2019). One downside to BECCS is the potential upwards pressure on food prices due to land competition (Muratori et al., 2016). Carbon sequestration as "intentional alteration of planetary-scale processes" falls under the category of geoengineering (Caldeira et al, 2013). Geoengineering also includes solar radiation management, discussed next.

Solar radiation management levers include cloud-seeding or aerosol injections (Caldeira et al., 2013). Solar radiation management strategies may reduce some hazards relatively quickly (Moreno-Cruz and Keith, 2013), but may create additional hazards due to complex climate-system feedbacks and can introduce additional trade-offs (Kravitz et al., 2018; Robock, 2020; Trisos et al., 2018). While solar radiation management strategies have yet to be tested in large-scale experiments, smaller-scale tests have been planned (Dykema et al., 2014). More research is needed to understand the implications of the rapid climate changes associated with solar radiation management and questions about shocks resulting from the termination of these strategies (Goes et al., 2011; Matthews and Caldeira, 2007; Trisos et al., 2018). Many solar radiation management strategies also cannot counteract some of the effects of greenhouse gas emissions, such as ocean acidification (Caldeira and Wickett, 2003).

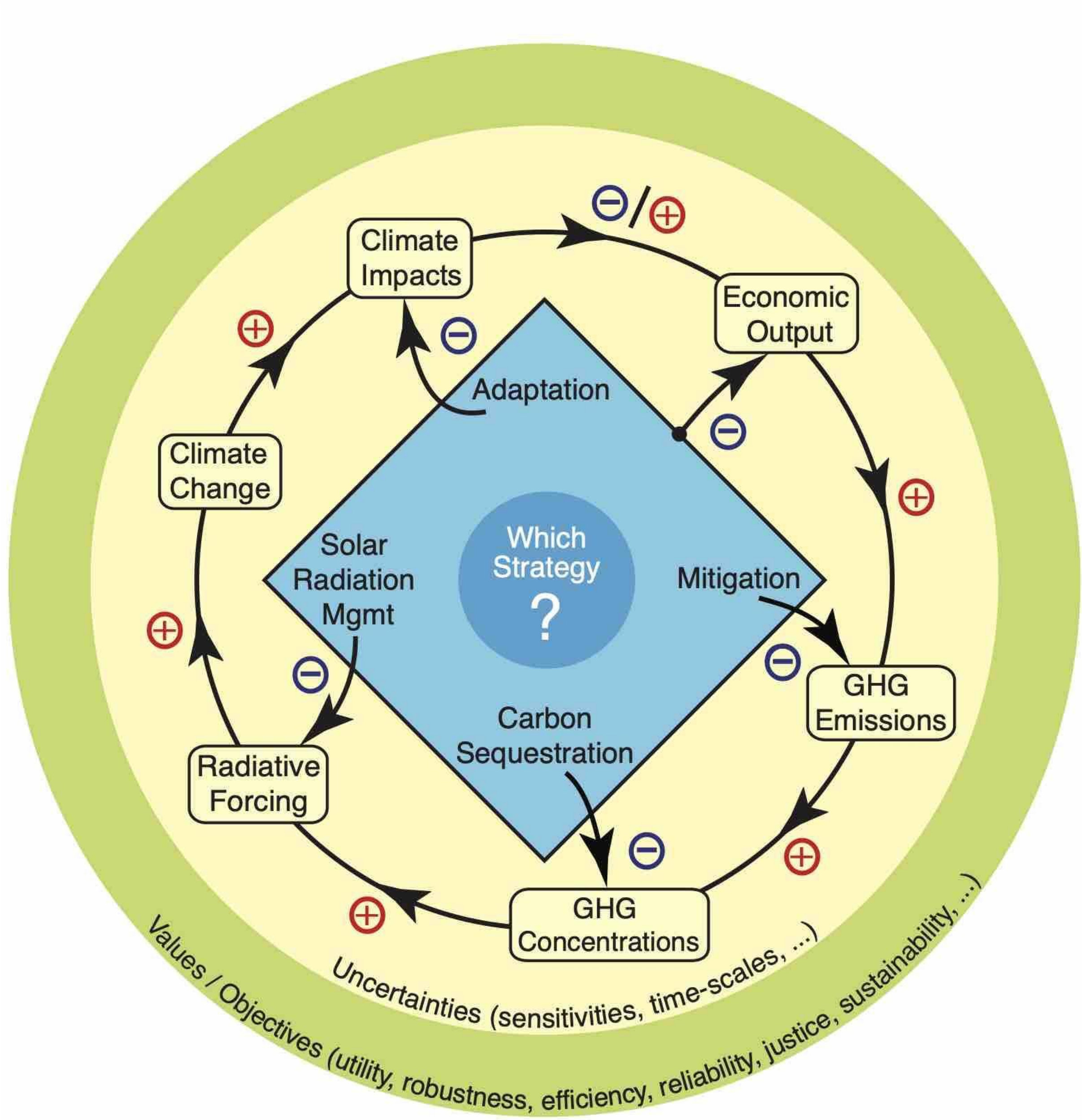

Figure 1: Climate risk management strategies can deploy a large number of decision-levers that generally fall into four broad categories (arranged inside the blue diamond): adaptation, mitigation, carbon sequestration, and solar radiation management. Each of these categories intervenes at a different point in the socio-environmental system (see the rounded boxes representing system components and

the black arrows with positive and negative couplings). Strategies for managing climate risks are confronted with deep and dynamic uncertainties (pale yellow field behind system diagram) and must navigate complex trade-offs between values and objectives (green field underlying everything). The negative coupling from the blue box of risk management levers to economic output approximates the direct costs required to implement the strategies. This figure is modified and expanded from (Caldeira et al., 2013).

3. Improving Climate Risks Management Requires Understanding Complex Coupled Systems

Identifying sound strategies to manage climate risks requires understanding complex coupled systems (Figure 1). In this section, we highlight three aspects of such systems: (i) a large number of potential levers that interact, (ii) multiple stakeholder constituencies with diverse values, and (iii) deep and dynamic uncertainties. All three push climate risk management into the category of "wicked problems" (Crowley and Head, 2017; Kwakkel et al, 2016, Moser et al., 2012; Rittel and Webber, 1973), a multi-faceted concept that highlights the difficulties of comprehensively formulating a problem and of defining what constitutes a good solution. "Wicked" problems contrast with "tame" ones, which feature clear system boundaries and unambiguous standards of success.

First, the number of potential actions is large and the actions interact. Consider, as an example, the question of how to manage coastal flood risks (Lempert et al., 2003). Potential decision levers include raising levees, diverting rivers, elevating houses, improving flood recovery, reducing greenhouse gas emissions, and solar radiation management (Fischbach et al., 2019; Moore et al., 2015; Schelfaut et al., 2011; van Dantzig, 1956; Xian et al., 2017). These levers span a wide range of spatial and temporal scales and impact a large number of values and objectives (Bessette et al., 2017; Groves and Sharon, 2013). This complex array of potential levers (interacting and with diffuse short- and long-term consequences) can drastically complicate a comprehensive formulation of the "whole" problem of managing coastal flood risk.

Second, diverse stakeholders can have different values that lead to divergent goals and priorities (Nordén et al., 2017) (see discussion in section 4.2). The coupled systems can exhibit trade-offs between key objectives (Herman et al., 2015). Different stakeholders that balance the objectives differently can disagree about what constitutes an optimal solution.

Third, strategies to manage climate risks face deep and dynamic uncertainties. Deep uncertainty refers to a situation "where the system model and the input parameters to the system model are not known or widely agreed on by the stakeholders to the decision" (Lempert, 2002). Decision-makers who adopt different assumptions about model structures and parameters may disagree about which strategies lead to which outcomes and can hence arrive at different preferred strategies even if their values and goals are the same (see discussion in section 4.3). Alternative model structures constitute different problem formulations, and in this way deep uncertainty challenges the notion of a definitive problem formulation (Kwakkel et al, 2016). The uncertainties are dynamic because decisions often play out over a considerable length of time during which new research and observations have the potential to change the uncertainties (often shrinking them, but not necessarily so) (Oppenheimer et al., 2008). Accounting for the potential for learning can improve strategies, but can be computationally and conceptually hard (Hadjimichael et al., 2020).

In this section, we have highlighted three features of complex coupled systems. We draw attention to these features because of how they complicate the task of *identifying* sound strategies for climate risk management. While identifying and assessing strategies is the focus of this article, we wish to emphasize that to manage climate risks, strategies must also be *implemented*. The features of complex coupled systems, and of the wicked problems they engender, can also challenge implementation by complicating communication efforts and the building of consensus in support of climate action (see, for example, the discussion in Moser et al, 2012). While these topics are beyond the scope of the article, we briefly address communication in section 4.6 and community engagement in section 4.7. Lempert and Turner (2020) illustrates one approach to incorporating the question of consensus-building into the analysis of risk-management strategies.

4. Challenges in Analyzing Climate Risk Management Strategies and Avenues to Tackle Them

The discussion, thus far, illustrates the complexity of analyzing strategies to manage climate risks. We now turn our attention to seven specific challenges and approaches to tackle them. While we review these challenges separately, they often overlap. We discuss avenues to account for these overlaps at the end of this section.

4.1 Linking the required disciplines

Complex socio-environmental systems comprise interacting components traditionally studied by separate academic disciplines. Knowledge and methods from across these disciplines must therefore be integrated in order to develop an understanding of overall system dynamics, project potential outcomes of strategies, and assess the desirability of those outcomes. For example, how we represent the global carbon cycle (a question addressed in the Earth sciences) interacts with how we represent long-term discounting (addressed in economics) in determining the economically efficient strategy for mitigating carbon dioxide emissions (Schultz and Kasting, 1997). Each discipline can "see" only a part of the problem, and combining improvements in multiple disciplines can lead to new insights. The disciplines involved in climate risk management span diverse branches of inquiry, including the natural, formal, and social sciences, as well as engineering, humanities, and decision science. Further examples of integration are found below, and we return to the linking of disciplines in section 4.7, where we provide a high-level sketch of some key pathways.

Some terminology can be helpful for communicating about this aspect of climate risk management when, for example, seeking to learn from others confronting similar challenges or to identify appropriate funding sources. Research that integrates knowledge and methods across disciplines is referred to as *interdisciplinary* research (Stock and Burton, 2011; von Wehrden et al., 2019). *Transdisciplinary* research and *convergence* research are related and overlapping concepts, variously defined as building on interdisciplinarity through even greater integration and synthesis across disciplines, collaboration with non-academic partners, or a focus on specific motivating concerns (e.g., "problem-driven") (Johnson, 2019; National Research Council, 2014; Sakao and Brambila-Macias, 2018; Stock and Burton, 2011; von Wehrden et al., 2019). Climate risk management fits each of these concepts and can benefit from the insights of a developing literature that collects and evaluates best practices for effective interdisciplinary, transdisciplinary, and convergence research (Freeth and Caniglia, 2020; Gaziulusoy et al., 2016; Institute of Medicine, 2005; National Academies of Sciences, Engineering, and Medicine, 2019; National Research Council, 2014).

4.2 Identifying relevant values and objectives

Values encompass all of the principles, perspectives, and concerns that people use to judge the desirability of potential actions and outcomes. In other words, values are why we care about risk. Vocabularies for discussing the treatment of values vary across research communities. Here we adopt the following definitions. *Goals* are what one is concerned to achieve in a given decision context. In the case of coastal flood risk management, goals may include minimizing loss of life, minimizing cost, maintaining a tax base, or distributing risk equitably. Goals can be seen as the result of values intersecting with the decision at hand. *Metrics* are proxies within the analysis that operationalize and quantify the degree to which a goal is satisfied by potential outcomes. Defining a metric for the goal of *minimizing cost*, for example, requires deciding what costs will be included and how they will be calculated and aggregated. Defining a metric for the goal of *distributing risk equitably* requires a mathematical description of equity. Finally, *objectives* mirror goals but with reference to metrics, so the qualitative goal of minimizing cost becomes a formal objective of minimizing a specific formula within the analysis.

Values are fundamental both to decision making and to the design of decision analyses (Clemen and Reilly, 2013; Keeney, 1992). Failing to attend carefully to values right from the beginning can lead to formulating—and ultimately solving—a problem that is not as relevant to the stakeholders. Stakeholder goals inform the initial scoping of plausible strategies for achieving those goals, thereby determining what strategies will be examined in more detail. Subsequent detailed assessment and comparison of strategies then requires characterizing potential outcomes in ways that reveal how each outcome stacks up with respect to those same goals. For example, in the case of coastal flood risk management, likely outcomes of a given flood wall design might initially be characterized in terms of an annual exceedance probability. But what does that number mean for property damage, loss of life, or equitable distribution of risks? Further analysis is required to estimate potential impacts in terms of metrics and objectives that mirror stakeholder goals. Consequently, values also inform the choice of scientific and decision-analytic models to be used within the analysis: an adequate model (Addor and Melsen, 2019; Haasnoot et al., 2014) will include system components needed to map strategies to outcomes, describe those outcomes at the spatial and temporal scales needed to estimate relevant metrics (Vezér et al., 2018), and support quantification of uncertainties associated with the objectives (Helgeson et al., 2021).

Learning about relevant values requires engagement between researchers and other stakeholders. There are many modes of engagement, from informal consultation and collaboration to more formalized advisory panels to research-based approaches like interviews, surveys, and focus groups (Phillipson et al., 2012; Reed et al., 2009). Deeply collaborative engagements are sometimes referred to as co-production (Norström et al., 2020). The question of who is included among the stakeholders deserves careful consideration (Colvin et al., 2016; Few et al., 2007; Tuana, 2020). Heuristic tools for collaboratively articulating values include values hierarchies and means-ends diagrams (Clemen and Reilly, 2013; Keeney, 1992). Frameworks for recognizing and structuring values include ethical theory (Mayer et al., 2017), psychometrically-validated taxonomies of values (Brown and Reed, 2000), and systems of cultural (Satterfield et al., 2013) and environmental valuation (Tadaki et al., 2017).

The values and goals that motivate climate risk management can be explored at different geographical scales and levels of specificity. At the global scale, and in very broad strokes, the Intergovernmental Panel on Climate Change (IPCC) summarizes myriad studies on the impacts of climate change into five key "reasons for concern'' (IPCC, 2018). As an example at the national scale, the development process of the United States Fourth National Climate Assessment included regional engagement workshops through which stakeholder values shaped the focus of the report (Avery et al., 2018). Regional- and community-level engagements can provide opportunities for richer and more comprehensive elicitation and characterization of relevant values (e.g., Borsuk et al., 2001; Wolf et al., 2013; Graham et al., 2018), and as a result, the potential for more targeted risk management analyses.

Situating values within a visualization of the risk management context is a common step in the framing of risk analyses and the design of their objectives. Influence diagrams (Clemen and Reilly, 2013; Howard and Matheson, 2005) map the paths through which a decision impacts the objectives and display the sequence of events when a decision maker will receive relevant information. Mental models (Morgan et al., 2002) use a similar visual language to characterize and compare understanding of risks, including their underlying mechanisms, and this approach can be extended to explicitly include values (Bessette et al., 2017; Bridges et al., 2013) (see Figure 2). Values are typically impacted through specific components of a system, and articulating this explicitly can aid the formulation of goals, their translation into objectives, and the mapping of objectives onto quantitative features of scientific and decision-analytic models.

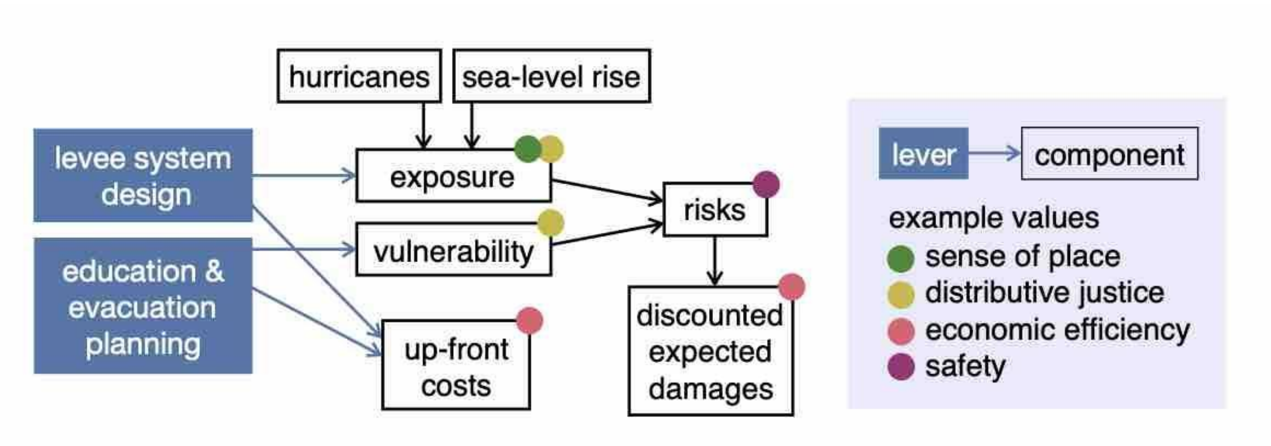

Figure 2: A didactic example of integrating stakeholder values into a visualization of system understanding to support the design of risk analyses. The example concerns coastal flood risk management (synthesizing and simplifying results from (Bessette et al., 2017) and (Mayer et al., 2017)). Arrows indicate the direction of influence among levers and system components. Colored dots indicate where stakeholder values may be realized in the system, which can guide the formulation of metrics and objectives within the analysis.

4.3 Identifying and quantifying important uncertainties

Climate risks depend on uncertainties (Schneider, 2002). Uncertainties can be classified as aleatory or epistemic. Aleatory uncertainties are those which are intrinsic to a stochastic process, such as whether a flipped coin lands heads-up or tails-up. Epistemic uncertainties result from a lack of knowledge about the underlying process, such as whether the coin is fair. In other words: epistemic uncertainty relates to the conceptual model while aleatory uncertainty relates to the effects of unresolved stochastic processes.

Epistemic uncertainties play a major role in climate risk management due to limited knowledge about future anthropogenic greenhouse gas emissions (Ho et al., 2019) and climate-system responses (Vega-Westhoff et al., 2020), as well as uncertainty about the structure and dynamics of the underlying socioeconomic or environmental systems. Uncertainty assessment can take the form of quantification or characterization, or a combination of the two. Uncertainty quantification describes uncertainties using one or more probability distributions, while uncertainty characterization typically represents uncertainties through the use of scenarios that are designed to capture relevant ranges.

Improving the representation of these uncertainties can considerably change (and often increase) risk projections (Lee et al., 2020). Characterizing the uncertainties surrounding the coupled natural-human system is nontrivial. For one, hazards driving large risks are typically rare events. Rare events are located in the tails of the distributions describing the outcomes. For example, tropical cyclones can cause storm surges that cause severe coastal flooding, but these high storm surges happen infrequently (Needham et al., 2015). Inferences about such extreme events can be difficult because they are—by definition—rare. As a result, projections of extreme events can depend considerably on structural assumptions (Van den Brink et al., 2005). This dependence of risk estimates on adopted model structure is an example of deep uncertainty. Risk projections can also hinge on subjective choices about model priors, how to represent past and possible future forcings, and which data sets to use (Srikrishnan et al., 2019; Wahl et al., 2015; Wong, 2018; Wong and Keller, 2017). Consider, as an example, projections of coastal extreme water levels (Figure 3). These projections change across a range of common assumptions about the potential nonstationary behavior of storm surges and the mechanisms driving ice-sheet dynamics (DeConto and Pollard, 2016; Wong, 2018). An additional challenge in uncertainty quantification is that climate risks are often driven by compound events (Raymond et al., 2020; Zscheischler et al., 2018). For example, a tropical cyclone can drive a storm surge, extreme inland rainfall, and damaging winds. Neglecting the correlations between these hazards can lead to biased risk estimates (Moftakhari et al., 2017; Wahl et al., 2015). Furthermore, models used to project hazards are often computationally expensive and have a large number of model parameters that need to be estimated. Characterizing the full joint probability density function of the model parameters in a way that resolves the decision-relevant tails can impose serious (and often computationally infeasible) demands (Lee et al., 2020). Last but not least, because humans are also a part of the system, projections of climate risk depend on changing human values, decisions, and actions (Schneider, 2002). For example, the timing of making decisions and implementing them are themselves uncertain and can impact outcomes (Colten et al, 2008, Keller et al, 2007, Singh, 2010).

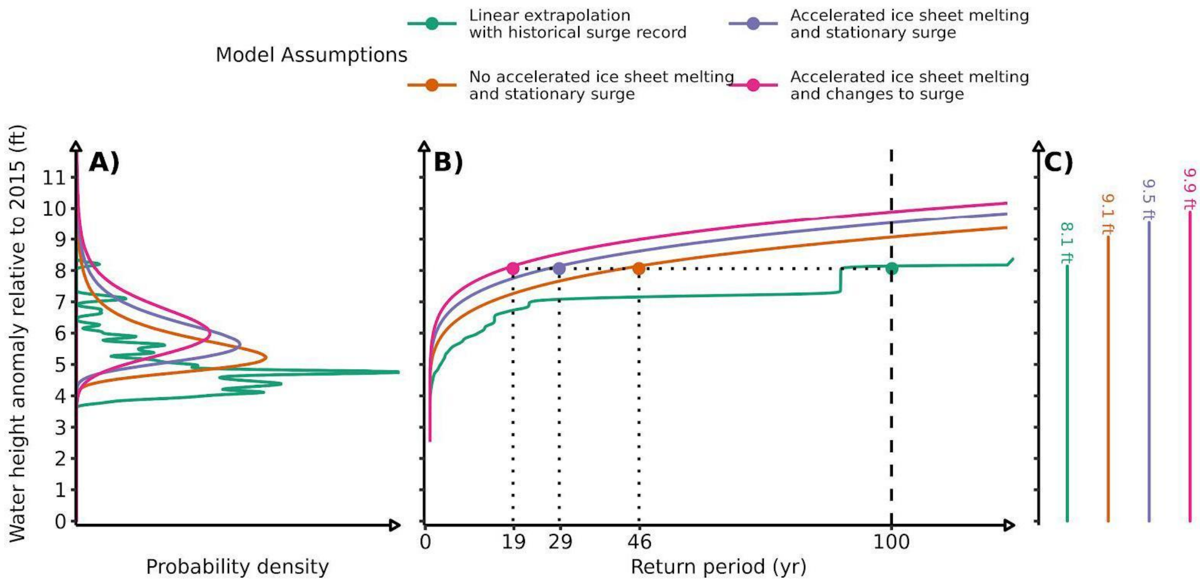

Figure 3: Structural uncertainty can drastically impact projected hazards, such as coastal flood risk, and risk management strategies, such as levee-building. In each panel, colors correspond to different models, each of which makes a different set of assumptions about future sea-level rise and storm surge dynamics. Panel A) shows how the probabilities of extreme water heights (sea-level rise combined with storm surge) in 2070 change as model assumptions are varied. Panel B) illustrates how changing model assumptions affect the return period (how frequently one might expect to see that event) of these extreme water levels. Panel C) plots the 100-year protection heights resulting from using the various models. If a planner were to base their protection level on the projected 100-year flood level obtained by using the simplest model (in green; 8.1 ft), the real level of protection might only be to a 1-in-19 year event if ice sheet disintegration occurs rapidly and storm surge distributions change in response to warming (in pink). Under these assumptions, a 9.9 ft levee would be required to protect against a 100-year event in 2070. Figure redesigned from (Srikrishnan et al., 2019).

Improving uncertainty characterization in the area of climate hazards is a fast moving field (Beven et al., 2018; Krueger et al., 2012; Otto et al., 2016). Active areas of research include approaches to refining (i) the characterization of deep uncertainties through expert elicitation (Bamber et al., 2019; Morgan, 2014; Zickfeld et al., 2010), (ii) the integration of observations and expert assessments into probabilistic projections through data-model fusion and probabilistic inversion (Bedford and Cooke, 2001; Fuller et al., 2017), (iii) the use of a hierarchy of models to improve mechanistic understanding while also sampling decision-relevant tails (Held, 2005; Wong and Keller, 2017), (iv) the characterization of compound hazards (AghaKouchak et al., 2020), and (v) the identification of decision-relevant uncertainties through sensitivity analyses (Lamontagne et al., 2019; Saltelli et al., 2019).

These five research areas discussed above can interact and provide synergies. This can be illustrated for the problem of projecting coastal flood hazards. Future sea-level rise—and hence coastal flood hazard—depends in part on the pace of melting ice sheets, but ice-sheet models that resolve key physical processes are computationally demanding and have many model parameters. Incorporating such models into tail-area risk estimates requires first estimating a large number of parameters; the number of model runs needed for this often exceeds available computational resources. One approach to address this is to build a computationally fast emulator of the expensive model, use this emulator to perform a full uncertainty analysis including all parameters, and then use a global sensitivity analysis to identify a subset of the most decision-relevant parameters (Conti and O'Hagan, 2010; Wong and Keller, 2017). The insights into which uncertainties matter most for decision-relevant metrics can then be used to refine and focus the uncertainty quantification.

For a case study of flood-risk management in New Orleans, a global sensitivity analysis identifies a small subset of parameters that drive much of the uncertainty surrounding projected flood hazards (indicated by the circles in Figure 4) (Wong and Keller, 2017). In this case, uncertainties surrounding storm surges and the Antarctic ice sheet dominate the picture. This ranking is broadly consistent with other related studies and, perhaps, intuition. The finding that the storm surge model (and especially the shape parameter) is highly important is consistent with a similar case study for a location in the Netherlands (Oddo et al, 2017). The high importance of uncertainties surrounding storm surges (relative, for example, to uncertainty surrounding glaciers and ice caps, see Figure 4) is perhaps expected, as projections about extreme events with relatively short observational records can be highly uncertain (Wong et al, 2018) and because changes in regional water levels due to projected storm surges can far exceed those due to projected melting of glaciers and ice caps (Bakker et al, 2017, Wong and Keller, 2017).

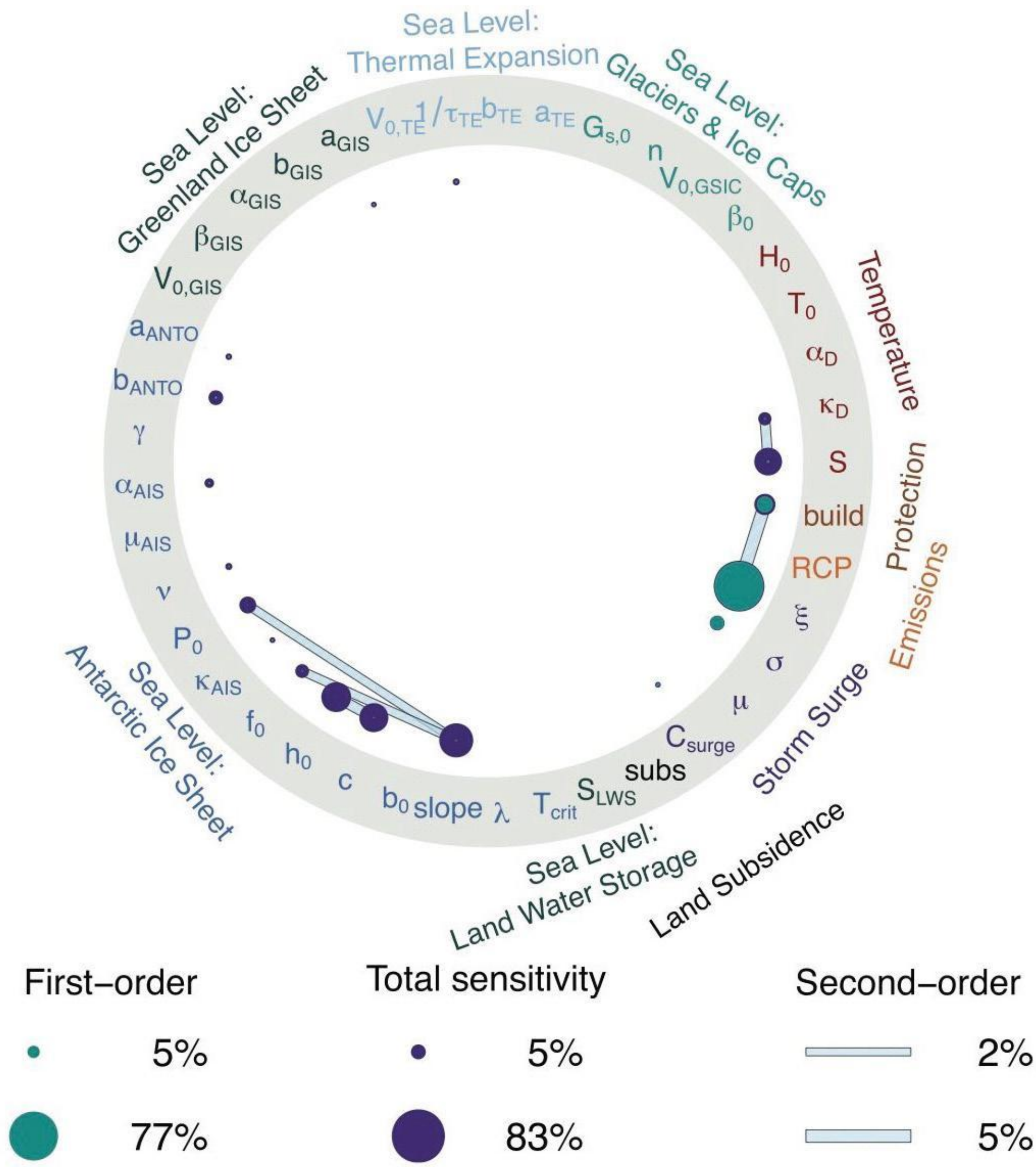

Figure 4: Quantification of the relative importance of key considered uncertainties for the uncertainty surrounding the projected flood hazards over the next few decades for a case study in New Orleans (Wong and Keller, 2017). The size of the circles represents the sensitivity of flood hazard to each parameter. The width of the connecting lines represents the sensitivity of flood hazard to parameter interactions. If a parameter has no circle, this indicates that the projected flood

hazard is not sensitive to its value. Figure adopted from Wong and Keller (2017)) without changes. For definitions of the parameter names please refer to Wong and Keller (2017). The figure is distributed under the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0) license.

4.4 *Resolving the interactions of decision-levers and system dynamics*

Climate risk management levers can interact with each other synergistically or antagonistically. As a synergistic example, climate mitigation can slow sea-level rise (Nauels et al., 2017), reducing coastal adaptation needs. On the other hand, adapting to higher temperatures by using air conditioning increases energy use and (absent a transition to low-carbon sources of electricity) greenhouse gas emissions (van Ruijven et al., 2019). This feedback results in a greater overall need for mitigation efforts. The early availability of negative emissions technologies may also result in reduced mitigation needs and investment (Holz et al., 2018; Muratori et al., 2016). As a result of such interactions, studying the impact of climate risk management levers in isolation can provide a myopic perspective.

Assessing climate risk and the potential performance of risk management strategies requires understanding the dynamics and interactions of the coupled physical, climate, social, and technological systems. The extent to which communities are exposed and vulnerable to natural hazards changes as people and institutions learn about local risk and adapt (Kreibich et al., 2005; Kreibich and Thieken, 2008; Work et al., 1999) (Figure 5). This decision-making, as well as the use of other levers such as mitigation, changes the joint system dynamics and risk profile. For example, an analyst might implicitly rule out relevant system dynamics, such as coupling across sectors or coupled natural-human interactions, by not including them in any of the used system models. This could affect projected outcomes and result in a divergence between the projections and realizations. In extreme cases, the inclusion (or removal) of these dynamics might change how the decision is made. There are also interactions across multiple sectors, such as agriculture, energy, and water, which can result in nonlinear system dynamics (Moss et al., 2016; USGCRP, 2018).

To illustrate these interactions, consider the task of projecting flood risks. Flood risk projections can depend on several coupled natural-human system interactions. Two interactions of note are the levee effect, where the building of flood risk mitigation structures causes increases in development and population growth in the protected area, and what might be called the abandonment effect, where the memory of recent flooding causes migration away from the floodplain (Di Baldassarre et al., 2013). These feedbacks can change the exposure from flooding hazards. In the case of a strong levee effect, the resulting increase in exposure might outpace the reduction in hazard resulting from the construction. The net result is an increase in risk from the project.

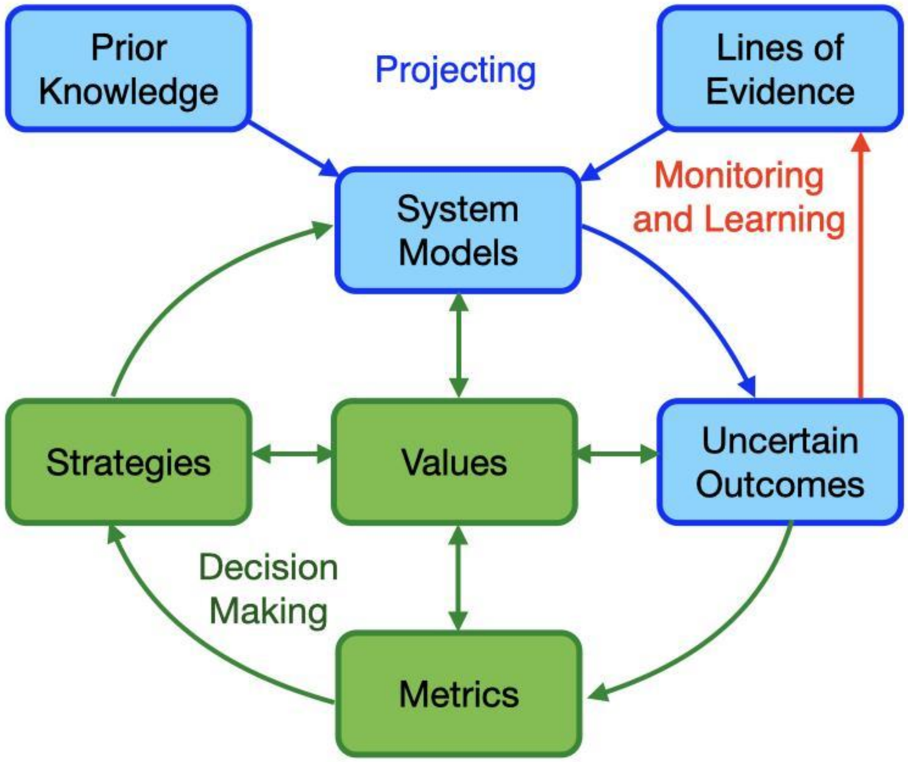

Figure 5: Interactions between the coupled natural and human systems can drastically change the system dynamics and the anticipated performance of a given strategy. A simplified model (denoted by the blue components and arrows) that misses factors and interactions related to human decision-making (represented by the green components and the red and green arrows) can miss important interactions and system dynamics.

4.5 Characterizing trade-offs and synergies between objectives

Climate risks affect diverse groups of stakeholders, who may have multiple, potentially conflicting goals due to varying values (Nordén et al., 2017). Classical approaches to decision-making under uncertainty optimize a single utility function, which is intended to aggregate relevant preferences (Morgan, 2017) (Figure 6). Aggregating varying and potentially conflicting objectives into a single utility function can miss tensions, obscure trade-offs, and implicitly prioritize certain objectives (Garner et al., 2016; Herman et al., 2015; Lempert, 2014; Moallemi et al., 2019).

Multi-objective optimization methods, such as multi-objective evolutionary algorithms (Coello Coello et al., 2007), identify a set of optimal strategies, called the Pareto front. Comparing any two strategies belonging to the Pareto front results in improved performance with respect to some objectives and decreased performance in others. The Pareto front reveals what performance levels are possible with respect to the considered objectives, allowing for preferences to be adjusted afterwards. For example, integrated assessment models of climate change can show a tension between the objectives of reliably limiting global warming and increasing economic consumption (Nordhaus, 1992). An example of such a trade-off is illustrated by the Pareto front in Figure 7 (Garner and Keller (2016).

Due to trade-offs between objectives, many different strategies can be identified which are optimal in the sense described above. However, the optimization procedure necessarily includes a particular representation of the underlying epistemic uncertainties. The choices involved in selecting a particular representation can result in solutions which appear optimal, but which degrade in performance when exposed to alternative representations, which are characteristic dynamic uncertainties. Ideally, we would identify strategies from the optimization which are robust to alternative characterizations of underlying uncertainties. In this context, a strategy is robust when it can achieve a satisfactory level of performance with respect to the selected objectives when confronted with relevant deep uncertainties (Herman et al., 2015). Multi-objective robust decision-making (Kasprzyk et al., 2013) is one decision framework which combines multi-objective optimization with testing of selected strategies for robustness.

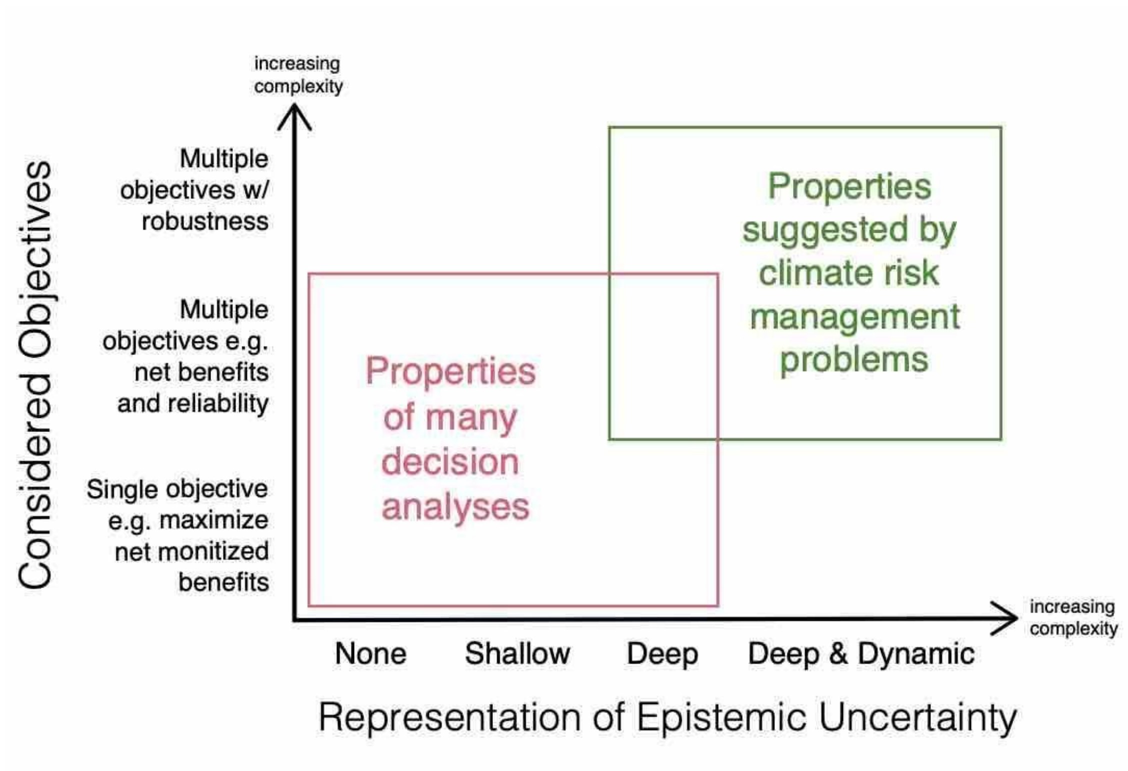

Figure 6: Designing and analyzing climate risk management strategies requires methods that are appropriate for the nature of the decision problem. The x-axis describes different levels of epistemic uncertainty representation, ranging from none (so only aleatory uncertainty is included in the analysis) to deep & dynamic uncertainties. The y-axis shows how the objectives considered by the analysis or suggested by the problem can be structured, from only considering a single objective (such as net monetized benefits or reliability) to multiple objectives with considerations of robustness to uncertainty. The green box highlights an area which

contains combinations of epistemic uncertainty realization and objective formulation suggested by the nature of many climate risk management problems. The pink box captures combinations which are properties of many decision analyses. These may exclude considerations of robustness or the dynamic nature of the deep uncertainties, potentially creating biases or failing to fully represent stakeholder values. Figure modified and expanded from (Singh et al., 2015).

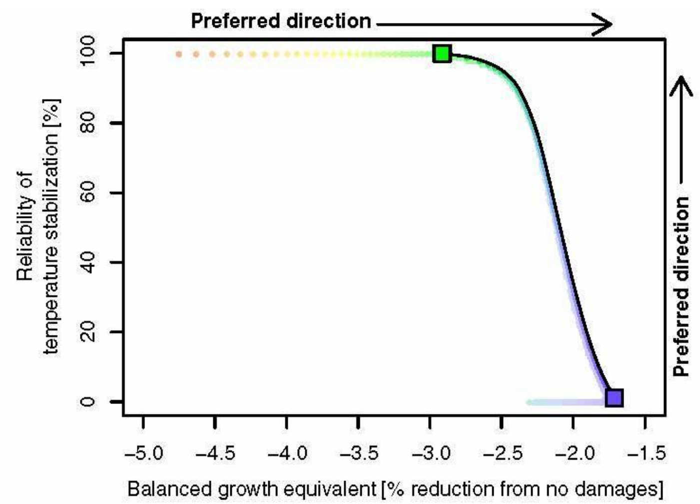

Figure 7: Example of a Pareto front characterizing the trade-offs between objectives. Each circular point corresponds to a different solution belonging to the Pareto front, while the squares correspond to optimal solutions when only considering one objective. The x-axis and the colors of each point represent the change in balanced growth equivalent from the no-climate damages scenario. The y-axis shows the achieved reliability of stabilizing global mean temperatures at the 2°C target set by the Paris Agreement. The preferred directions (reduced damages and increased reliability) are shown by the arrows on the top and right sides of the plot. Decreasing economic damages beyond a certain threshold requires reducing

the reliability of temperature stabilization, and increasing temperature stabilization reliability is associated with increased economic damages. Identifying the Pareto front allows decision-makers and stakeholders to see the trade-offs between their considered objectives and how their constraints map to achievable outcomes. Figure adopted without changes from Garner et al. (2016), distributed under the Creative Commons Attribution 4.0 International License (http://creativecommons.org/licenses/by/4.0/). See Garner et al. (2016) for details.

4.6. Communicate effectively to inform decisions

Informing decisions requires communication with decision makers. The scope and reach of climate risks means that these decision makers are a diverse group, spread across the public and private sectors at organizational levels from individuals to global bodies.

The communication side of climate risk management is a sprawling area of study in its own right, discussed under overlapping headings such as climate services (Vaughan et al., 2018), risk communication (Morgan et al., 2002), and decision support (Matthies et al., 2007; National Research Council et al., 2009). Here we can highlight only a few key points. First, attempts to improve decision making implicitly invoke some notion of what it means to make a *good* decision (Elwyn and Miron-Shatz, 2010), which raises issues of agency, manipulation, and other ethical matters (Adams et al., 2015). Second, the impacts of decision support tools and climate hazard information on decisions is complex and requires evaluation (Budescu et al., 2014; Clar and Steurer, 2018; Wong-Parodi et al., 2016). This evaluation is, however, often neglected (Clar and Steurer, 2018; Morgan et al., 2002; Vaughan et al., 2018; Wong-Parodi et al., 2016). Third, informing real-world decisions can raise nontrivial questions at the interfaces between fields such as law, ethics, political science, and decision-analysis (Kopp et al., 2019; Scolobig, 2015).

4.7 Learning from decision-making needs to inform research designs

Analyzing decisions about how to manage climate risks can help to identify mission-oriented basic research questions (Bakker et al., 2017; Hekkert et al., 2020; Stockes, 1997). Identifying research relevant to the mission of improving climate risk management requires integrating the elements discussed above into a unified, coherent, and iterative process that can flexibly incorporate stakeholders, decision-makers, and analysts. There is a large body of literature on how to design such a process (Field et al., 2014; Haasnoot et al., 2013; Kates et al., 2012; Lempert et al., 2003; McDaniels et al., 1999; McDaniels and Gregory, 2004; Moallemi et al., 2019; Moser et al., 2012; National Research Council, 1999; Renn, 1999; Wong-Parodi et al., 2016). Here we focus on key elements and linkages to present an example process schematic illustrating paths of interaction and iteration (Figure 8).

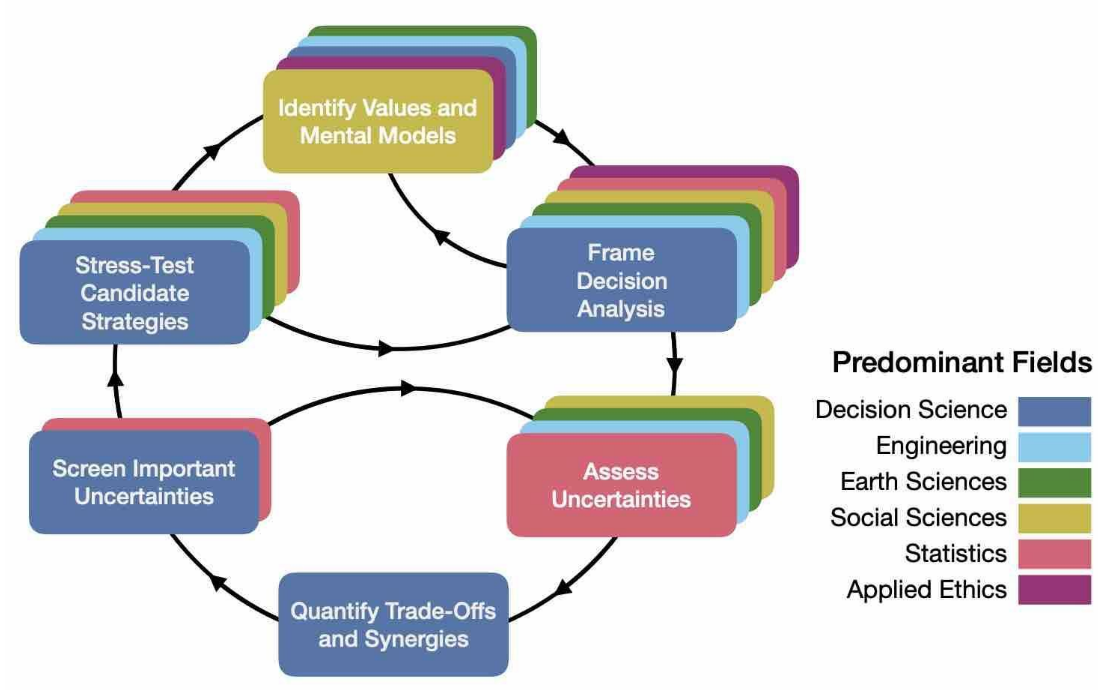

Figure 8: Assessing and designing climate risk management strategies, and identifying mission-oriented research questions, requires an iterative approach (represented by the arrows) that links concepts and tools from a wide range of disciplines (represented by the different colors of the boxes). This figure synthesizes and expands on concepts in the studies discussed in this subsection.

This example process starts with identifying values and mental models of stakeholders, decision-makers, and analysts. It then uses this information to jointly frame the decision analysis, including specification of the decision-levers, uncertainties, and metrics to be considered, as well as the relationships (formalized in models) that connect these elements. The next step is to quantify uncertainties, if needed using reduced complexity models or emulators. This step then informs the analysis of trade-offs and synergies between the objectives. The next steps in this iterative loop are to screen for decision-relevant uncertainties and to stress-test candidate strategies. The insights from these steps can point to further uncertainties as well as help refine the assessment of values and mental models, which may in turn motivate revisions to the problem framing. Of course, this is a drastically simplified overview that abstracts from many important considerations (see references in the previous paragraph for further advice and process schematics).

5. Conclusions

Climate risk management includes many challenges, including deep and dynamic uncertainties, diverse (and sometimes conflicting) stakeholder values and goals, and complex system dynamics. These aspects of climate risk management problems result in a need for fundamental research that integrates disciplines and researchers with stakeholders and decision-makers.

We review how basic research can inform decision analyses of climate risk management and how these decision analyses can, in turn, inform research designs. Currently available data, tools, and approaches have enabled valuable insights and helped to improve decisions, but important challenges remain. Adopting an iterative and integrated approach to climate risk management can lead to important new insights, provide more relevant decision analyses, and identify avenues to improve risk management strategies. Such an approach can help to link the required disciplines, identify relevant values and uncertainties, resolve key system dynamics, characterize trade-offs and synergies, communicate effectively, and inform research designs. In short, a sound approach to climate risk management is required to do the science right and to do the right science (Tuana, 2018).

Summary Points

1. Climate change drives nontrivial changes in hazards and risks.
2. Climate risks are subject to deep and dynamic uncertainties.
3. Designing a climate risk management strategy often requires navigating trade-offs between diverse and often conflicting values and objectives.
4. Analyzing climate-risk management decisions can identify mission-relevant basic research questions.

Future Issues

1. How to train stakeholders, decision-makers, practitioners, and researchers in the required disciplinary and collaborative skills?
2. How to design, implement, and sustain the required decision support and observation systems?
3. How to establish and support an environment of shared discovery that enables the required collaborations?

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