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Decision-Making for Managing Climate-Related Risks: Unpacking the Decision Process to Avoid "Trial-and-Error" Responses

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We provide an overview of decision support tools and methods that are available for managing climate-related risks and for delivering adaptation and resilience options and solutions. The importance of understanding political, socio-economic and cultural contexts and the decision processes that these tools support is emphasized. No tool or method is universally suited to all circumstances. Some decision processes are structured with formal governance requirements; while others are less so. In all cases, discussions and interactions with stakeholders and other players will have formal and informal aspects. We categorize decision support tools in several broad ways with the aim of helping decision makers and their advisors select tools that are appropriate to their culture, resources and other circumstances. The assessment examines the constraints and methodological assumptions that need be considered.

Keywords: climate change, risk management, climate governance, cynefin, climate mitigation, climate adaptation, decision analysis

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INTRODUCTION

Climate change only differs from other risk management problems by the fact there is only one Earth and a number of the risks are existential to life on the planet. But it is still about managing risk, for which there is an immense body of literature and decades of experience to draw upon; the wheel need not be reinvented. Risks (Simpson et al., 2021) can be directly related to greenhouse gas emissions, such as the risk related to exceeding an average increase in air temperature since preindustrial times of 1.5°C, or indirectly related to that, such as health outcomes from a warming climate (Vanos et al., 2020) (see **Box 1**). Further, climate risks may also relate to risks from actions used to ameliorate other risks.

Deciding on actions to ameliorate climate-related risks is a very human process; many psychological factors may impact on the cognitive and deliberative processes of individuals and organizations (Orlove et al., 2020). These factors play important roles in making sense of the problems to be tackled and in the final decisions on what actions may be taken. They can also influence choices (decisions) on the types of methods to employ to inform decision-making. Actual methods, tools and processes for making decisions on climate change are not often discussed, except in a macro sense, when talking about how to manage climate change, as if the solution and the problem are inextricably linked and seemingly obvious. Yet managing risks, particularly indirect ones, may be achieved through many different pathways, many of which may involve great uncertainty, and which will have varying benefits, costs and effectiveness for ameliorating risk. A decision-maker may potentially have leanings to one or a few of many options, depending on their own preferences, which may not be in the interests of everyone. Moreover, individual steps to manage climate risks will have varying degrees of reversibility, potentially locking in future pathways. How can errors of judgement be reduced, and poor outcomes avoided as far as possible?

A climate management process is more likely to require iterative approaches over many years, if not decades, because a number of risks are expected to emerge in the future and actions are needed now in order to take effect to reduce risk before the future arrives. While "trial-and-error" processes may be a necessary option for managing emergency responses to extreme events, it is not an option for timely mitigation intended for limiting global mean temperatures to not rising above 2°C (IPCC, 2018). Nor is it an option under many circumstances where individuals, communities and sectors may be seriously disadvantaged by a proposed action. So what decision methods are available that could be brought to bear in resolving and deciding on (locally, regionally, globally) the best courses of action to tackle climate change, adapt to the challenges that are unable to be avoided, and enable the greatest chance for climate recovery and resilience of natural and human systems? More importantly and bearing in mind the human influences in process and outcomes, how might the complexity of the interactions of different risks (Simpson et al., 2021) be unpicked and made relatively straightforward in order to appraise how best to tackle the problem with limited resources, and many competing interests and perspectives?

In effect, risk management under climate change is the same as managing a nested "control system" (**Box 1**). The outer system is Earth's climate, with inner systems in Earth's regions, and progressing further inward toward locations (cities; or, in nature, ecosystems), and specific instances (houses, households and individuals; forests, glades and colonies). At whatever level, the principles of a control system can apply. It is not just a top-down process, defined as measures or regulations adopted by governments or corporate bodies, but includes bottom-up processes where actions can be taken by individuals or collectives of individuals with a mind to "think globally-act locally". There is an interaction within and between these levels to achieve an effective control system at any level. Decision-makers need to be aware of these interactions in order to provide effective responses; the degree to which the interactions need to be made explicit will depend on the scale of response being considered. Also, they need to be aware that, unlike a readily-understood control system such as a thermostat, adjustments (or iterations) will be needed along the way to correct the trajectory, rather than allow overshoots and a need for subsequent correction and restoration.

Decision processes do not have a uniform structure. The circumstances surrounding decisions may differ in many ways. There may be a range of uncertainties involved, differing in character and scale (see **Box 1**, **Figure 1**, **Table 1**). For climate change, the issues may relate to protecting a small locality or community or perhaps adapting a region or continent; and the potential consequences of the decision may vary from something quite moderate up to very significant, perhaps existential. The people involved can vary from a single decision-maker to several decision-makers, or in the climate change context often local or national governments with a plethora of stakeholders. The objectives may be unclear at the outset, often contentious among the decision makers and stakeholders. Experts may disagree in their advice, and data to resolve their differences may be sparse. The formal governance structures which dictate who should decide, and their responsibilities, authorities and accountabilities, can constrain the decision-making considerably, including the formal interactions with stakeholders. At the same time, availability of social and more traditional media ensures that informal debate among all players – decision makers, stakeholders, experts, and decision analysts – and the public will take place beyond the formal decision process creating expectations and even bottom-up actions, yet also providing a lot of relevant and useful information. Against such a breadth of circumstances, it is inconceivable that a single decision-making tool will be suitable for all cases: although some proponents of a method or software application might suggest otherwise in their marketing. People seeking to manage responses to the climate challenges amongst a portfolio of other challenges can find linking tools to tasks within their context a challenge in itself.

Here, we recognize that decision-making for managing climate-related risks is most likely to be unorganized, unstructured and, in simple terms, messy at the outset. However, many risks need to be managed by a collective of people, using processes that enable collective and repeatable outcomes, whether they be through communities, businesses and industries, civil society groups, and governments. The more often the processes are predictable and repeatable, the more they can be used by others in similar contexts. We lean to decision analytic approaches that can navigate the complex nature of risk management and make explicit the nature and background of a decision.

Our aim is *to provide an overview for policy-makers on what tools may be useful to support decision-making in managing climate-related risks, recognizing the complexity of the issues both in the physical world and the socio-political world in which the decisions have to be made*. In doing so we also provide a guided literature review, both directly and through many of our citations. Decision-making (hereafter DM when used as an adjective) literature specifically oriented toward "climate change" is sparse (**Figure 2**). We separate DM literature from other literatures that may relate to the causes and drivers of the phenomena that underpin understanding the risks; we seek literature specifically related to the decision process. A broader literature on decision-making tools is used in this overview, with links to experience in their application to climate-related DM. While we do not undertake an exhaustive and systematic review, we have covered sufficient breadth for the reader to find examples of the application of the main DM tools and techniques available.

The first part of our overview relates to framing decision-making. We identify the components of making decisions to respond to climate risks in a timely manner; some components of decision-making may have greater importance than others depending on the context for the decision-makers. By doing

BOX 1 | Example of climate-risk control systems-managing risk of heat stroke in elderly people.

Heat stroke in elderly people is a well-established phenomenon during heat waves (Vanos et al., 2020). Care for immobile elderly people at home during elevated heat, such as in heatwaves or during summer in many parts of the world, has many factors to consider. Thermo-regulation in a patient can be assisted by reducing heat in the vicinity. Both of these are examples of control systems in which the carer can actively make decisions and facilitate immediate outcomes.

A control system has a target condition for the state of the system, a controller (regulator), and a mechanism for changing the state of the system. The controller measures the state of the system, compares that measurement with the target condition and adjusts the controlling mechanism to move the state of the system toward the target condition.

A thermostat in an air conditioner managing the temperature of a room is one such control system on which the carer may depend. Thermoregulation in a human body acts in a similar way. Under heat stress, the body reduces heat by increasing blood flow to the skin where heat can dissipate into the air. In addition, cooling is achieved by the evaporation of sweat. Heat transfer is more effective as the room temperature falls below body temperature. Evaporation can occur in situations warmer than body temperature but its effectiveness is limited by humidity. Thus, room temperature and humidity are important for managing a patient's heat stress. For simplicity, we combine these terms as "the cooling environment".

The cooling environment of a room is dependent on that environment throughout the building, the surrounding city and the climate generally. Humidity is difficult to reduce passively and is a product of passive cooling in the larger urban environment. The thermal masses of buildings and cities create prolonged, elevated ambient temperatures that reduce the effectiveness of temperature control systems within individual rooms and homes, which have to work against continued radiation of heat from the thermal mass as well as simply reducing air temperature in a room. Each of these levels of thermoregulation are control systems that work on different temporal and spatial scales and involve different types and scales of decision processes. The interaction between them is illustrated in **Figure 1** and described in **Table 1**.

The management of an individual patient is dependent on, *inter alia*, historical developments of the ambient conditions in the building (months to years), the ambient conditions in the city (years to decades), the ambient climate (multi-decades to centuries) and his or her family/social support systems. Although history in buildings, cities and climate are not likely to have considered the issue of risks of heat stroke, they are still systems to which controls can be applied, i.e. the use of feedbacks to make adjustments to the conditions. Feedbacks in these control systems outside the home will not benefit the immediate conditions of the patient but will benefit the management of risks of heat strokes in future patients. In terms of decision systems, the outer control systems are more diffuse, less determinate, both in the controller and in the mechanisms for control. The controllers involve more people with varying social and family connections to the patient, more backgrounds, expertise, and experiences, and may be less likely to have continuity of people over the course of an iteration of feedbacks. The mechanisms for control become less likely to be a single action from a choice among actions (top down) but more likely to be many diverse actions (top down and bottom up) along interacting pathways with feedbacks increasingly occurring in a haphazard and diffuse manner. This diffusivity creates the perception that the outer systems are not control systems when in fact they are just unavailable for many people, or, when available, are under-utilized and misunderstood when not considered as control systems to manage risk.

Importantly, there is no single approach that could be prescribed to manage the risk of heat stroke in the patient. It would be easy to suggest all homes have highly efficient, high powered air conditioners. However, this is dependent on the owners having funds to purchase and operate such machines, the building and city having reliable power systems to service spikes in and/or prolonged use of the air conditioners, and that the climate is such that it does not cause power outages at these times through lightning strikes.

so, we aim to provide a framework in which the context for decision-making can be better understood and the tools better utilized. The second part is about the decision process, presenting phases of and approaches to the process. In particular, we then catalog several decision-making tools in ways that should enable individuals, communities, organizations and government departments and agencies identify a small number that may suit their needs in relation to climate change adaption and mitigation. We aim to help problem-solvers and their advisors become "intelligent customers" of decision analysis. We make no claims that our advice is objective in any sense; any catalog requires judgement to classify each item. However, we hope that we have written this paper in a way that catalyses a "pause for thought" so that users will better understand the various ways to make a decision utilizing a suite of available methods and tools. Lastly, we provide some insights from our experience on the road ahead for managing the climate challenges.

FRAMING DECISION-MAKING

Approaches to Making Decisions

The majority of our decision-making is informal, barely structured with little explicit deliberation and made in ways of which we may be barely conscious; of course, the majority of our decision-making concerns things such as when to eat lunch or the route to take across a station concourse. Consideration of the consequences of different outcomes may be barely noticeable. The degree to which risks may be considered depends on how "lucky one feels", which is an important motivator as to whether systematic approaches are used (risk aversion) or not (risk tolerant). In this case, risk aversion is less about fear and avoidance but more about determining that the consequence of a risk being realized cannot be tolerated. More systematic approaches may be something like needing to get to a meeting on time and considering the timeliness of different options for routes across the city. For significant decisions and in a professional context, we usually seek to make our decisions more formally, more "rationally" ("blind luck" is not an option), and in an auditable way, perhaps supported by some form of decision analysis and evidence. In groups we deliberate and seek to resolve differences of views. In organizations and governments there are formal governance rules and constitutions determining the decision processes, authorities and accountabilities; but alongside these, informal discussions inevitably take place, influencing the outcome.

That any form of decision analysis necessarily imposes some form of consistency and rationality upon the explicit modeling of the objectives and uncertainties is often not appreciated. Moreover, the consistency and rationality assumed by some approaches may contradict those assumed by others, making

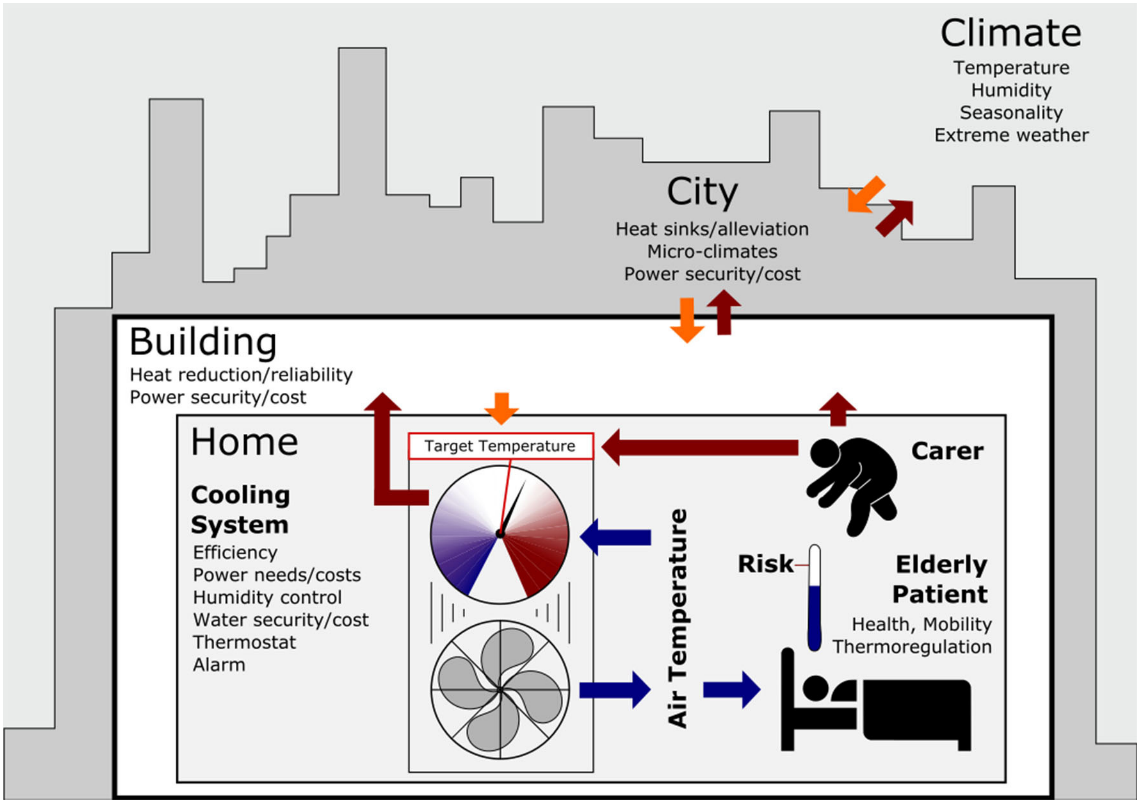

FIGURE 1 | Nested-control system managing the risk of an elderly patient experiencing a heat stroke during home care. Coupled inner systems of thermoregulation in the patient and the cooling system in the home can be regularly monitored and adjusted by a carer. The home environment is impacted by the ambient temperature and humidity of the building, which is the next outer control system. In turn, the building is affected by two further control systems - the temperature and humidity of the city, which is influenced by the regional climate. The identified risk (red line) in the patient thermometer is when the patient's temperature increases to a critical level at which heat stroke would occur. The cooling system is regulated by the difference in the room temperature and the target temperature (blue-arrow control system). Orange arrows indicate the primary direction of "passive" influence of temperature and humidity from the outer control systems to the inner control systems. Red arrows indicate the "active" feedbacks between these systems when the risk (probability of a temperature causing heat stroke) is unsatisfactory—adjusting the target temperature on the cooling system and the performance of the cooling system are unable to maintain satisfactory room conditions. Factors to consider in each control system are shown in small text. The carer, tenants of the building, building owners, city governors and international governors play critical roles in linking the different control systems through bottom-up and top-down processes.

the use of some tools incompatible with the use of others. Thus users need to check that they not only understand but agree with the assumptions underpinning those methods that they adopt, or they may be misled by or misuse the results. A very important aspect that distinguishes methodologies of decision analysis is whether they seek to be objective or instead render subjective judgements explicit, taking into consideration diverse values and uncertainties. That said, the application of any method, whether its assumptions fit with the users' perspectives or not, stimulates discussion and focuses attention on understanding the issues, and that alone can be enormously beneficial.

Informal decision-making may not naturally satisfy many of the assumptions made by a decision analytic method. The simplistic response is that informal decision-making is about securing an outcome that may not be easily justified, and that formal decision-making embodies principles to ensure that important decisions are made soundly and rationally. However, in practice, informality and formality run side by side and can be more harmonious, making it not quite so easy to make such a ready distinction (Hodgkinson and Starbuck, 2008; Gregory et al., 2012; French and Argyris, 2018). At the individual level, Kahneman, Tversky and many others have investigated the differences between informal and formal decision making (Kahneman and Tversky, 1974; Morton and Fasolo, 2009; Kahneman, 2011; Montibeller and Winterfeldt, 2015). For many years this work was discussed under the general heading of heuristics and biases, recognizing that informal decision-making uses "quick and dirty" heuristics to make choices, but at the risk of biasing choices on average away from what various principles of rationality would suggest. More recently, the terminology has changed to talking about:

System 1 Thinking intuitive, somewhat superficial and on the fringes of consciousness leading to potentially flawed or biased choices;

System 2 Thinking explicit, more analytic patterns of thought, auditable, leading the more consistent and rational decisions.

TABLE 1 | Example Attributes of the nested-control systems influencing the risk of an elderly patient experiencing a heat stroke during home care (lists are not exhaustive).

	Patient body	Home	Building	City	Climate
Controller (decision-maker)	Carer (external) Hypothalamus in the brain of the patient (internal)	Target temperature determined by carer (external) Thermostat (internal)	Tenants (internal; bottom up) Corporate body governing building (external; top down)	Legislature (top down) residents (bottom up)	Multinational agreements (top down) National, regional governments (top down and bottom up) Citizens (bottom up)
Mechanism for control	Sweating Skin exposure to air Drinking water bathing	Air movement for evaporation Cooling air	Building modifications and cooling options Tenant contribution to cooling building	Modifying city and street scapes for reducing thermal accumulation, storage Requirements for future buildings and infrastructure	International agreements Regulations Individual actions to reduce greenhouse gases
Indicators for action	Core body temperature Skin color Sweating Body hydration	Temperature Humidity Air flow	Building: • Ambient temperature and humidity • Thermal content and radiative energy potential • Surface reflectance to prevent heat absorption	City and street scape: • Ambient temperature and humidity • Thermal content and radiative energy potential • Surface reflectance to prevent heat absorption	Regional trends in climate and extreme events Conditions in cities
Time frame for actions	Minutes	Minutes to Hours	Months to Years	Years to Decades	Decades to Century
Dependencies	Patient health, weight Availability of suitable water	Capacity of cooling system to achieve requirements Security of power supply	Building materials, cladding and insulation Security of power supply	Building and infrastructure materials, cladding, surface texture and color, insulation. Vegetation and open water Security of power supply	Regional environment and physical climate/weather processes

Whether there is a true dichotomy here is moot and there are many other subtleties discussed in the literature (Shleifer, 2012; Evans and Stanovich, 2013). However, this simple distinction is sufficient for our purposes. Decision analysis seeks to encourage System 2 Thinking, helping decision-makers, their advisors and stakeholders each individually think through and reflect on the issues. However, it is easy in discussions and specifically in articulating probability and value judgements, to slip into System 1 Thinking. Better methodologies and tools have elicitation processes for nudging and challenging participants to think carefully and explicitly when giving judgements, but weaker ones simply take the responses and build them into the analysis.

Most decisions are made by groups and there are informal and formal aspects to their interactions and deliberation. Sometimes a decision is reached by simple discussion and consensus, or maybe an informal vote. Other times, "horse-trading" and other agreements can connect decisions ("… and you vote with me next time"). Less democratically, there may be a dominant leader who influences agreement with their views. Business, organizational and political/government decision making are bound by more formal governance structures and constitutions, which prescribe who can take part, what interactions are allowed, how stakeholders may have their voice heard, voting systems, etc. In many societies, decision-making has become more inclusive with stakeholders and the public being consulted formally (Bayley, 2008; Renn, 2008; Rios Insua and French, 2010). This is particularly true in the environmental domain in which many modern techniques of stakeholder engagement, public participation and deliberative democracy have been developed (Beierle and Cayford, 2002; Gregory et al., 2012). Alongside such inclusive deliberations, inevitably informal discussions are also influential. In businesses and organizations, these may be no more than "water-cooler" conversations; but the advent of social media has allowed much wider, often very influential discussion to take place for all types and scales of decision-making. To parallel the distinction between System 1 and 2 Thinking, French and Argyris (2018) have introduced the terminology:

System 1 Societal Deliberation informal discussion with no formal governance between decision-makers, stakeholders, experts, and others concerning a decision;

System 2 Societal Deliberation formal deliberations and decision-making set within explicit governance structures and constitutions which define who may take part, their responsibilities, authorities and accountabilities.

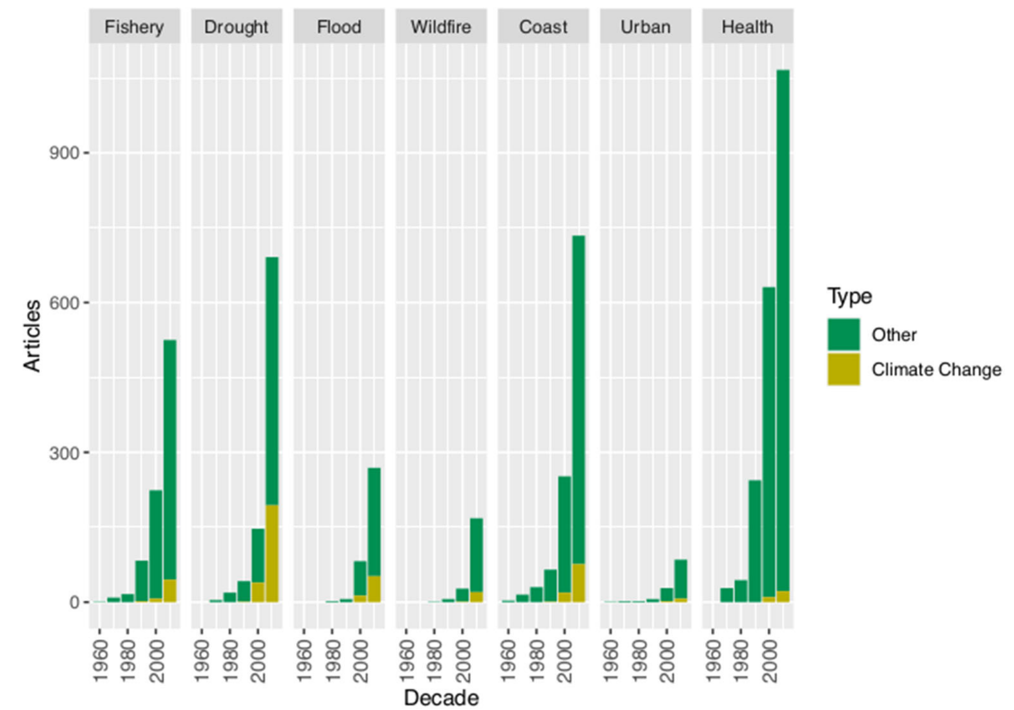

FIGURE 2 | Number of journal articles (per decade) on decision-making and risk management found in the literature database SCOPUS in each decade for seven climate-related risks, with the number specifically related to "climate change" indicated. Journal Articles were found by searching abstracts using the search "ABS ({risk assessment} OR {risk management} OR {decision making} OR {control system} OR {decision system}) AND (risk)", where the risk was Fishery (extended search term – "fishery OR fisheries"), Drought ("drought"), Flood ("flood management OR flood mitigation"), Wildfire ("wildfire OR wild fire"), Coast ("coast"), Urban ("urban environment"), or Health ("public health").

Decision analysis is aimed primarily at supporting System 2 Societal Deliberation helping those charged with the responsibility of taking the decision to do so in an informed, auditable and explicit way. It should, however, recognize the information sources provided by System 1 Societal deliberation such as social media, from which the decision-makers can learn about stakeholder values and other perspectives on the issues, thus ensuring that they are aware of breadth and depth of the issues that they face. Indeed, decision analysis can help in using its tools to communicate the decision-makers' reasoning to their stakeholders, particularly in the formulation and implementation stages of decision-making (French et al., 2005; Morton et al., 2009). In more inclusive decision-making, decision analysis can articulate discussions between decision-makers, stakeholders and experts, drawing the System 1 Societal Deliberations into the formal System 2 process (Mustajoki et al., 2004; Gregory et al., 2012; French and Argyris, 2018). It is important to recognize that broad processes which support this transition to System 2 Thinking and Social Deliberation are context dependent and depend on the skills of the analysis teams rather than something that can be achieved in an almost mechanical way alongside the modeling, computations and analysis. Effective decision analysis requires many more diverse skills than some mathematical and algorithmic introductions to decision analysis suggest.

Modeling and Decision Analysis

Decision analysis requires two forms of modeling. First, there is a need to model the external context and the physical issues being addressed; in our case, some climate change impacts. Such modeling is descriptive of the context and can be validated empirically if there are data available, though in many examples of risk management and mitigation, preventive actions are needed before full data may become available. Such models are constructs of two or more entities and the relationships and influences between them. In managing risks, the model may simply be: "if we choose to undertake this action to ameliorate the unacceptable risk, then these consequences will arise because of these reasons." This model may be founded on the professional judgement of decision makers and their experts or more empirically-based. Options for actions may be further elaborated by alternative beliefs or observations relating actions, the system being managed, and the consequences. The model can be made more robust by assembling knowledge relating to:

- What are the drivers of the risk and how might it be ameliorated?
- What makes the risk unacceptable?
- How specific does the action need to be described in order to fully understand the consequences?
- How does the action interact with the system to deliver consequences?

BOX 2 | Illustrative model for managing the risk of damage from extreme floods.

Climate change is increasing the likelihood of extreme flooding and, therefore, increasing the risk of accumulated damage from floods in low lying communities (Tabari, 2020). A number of actions through governments may ameliorate this risk in a low-lying area, either through mitigation (reducing greenhouse gas emissions), direct interventions (reducing exposure by increasing flood water storage, building levee banks or moving low-lying communities to higher ground), reducing vulnerability of exposed communities (reducing the effects of exposure in buildings and infrastructure or increasing capacity to recover), or creating incentives or a policy/regulatory environment that stimulates individual or private sector investment in reducing exposure and vulnerability.

Figure 3 presents an illustrative model of the management world and the real world in which human and natural systems interact. The management world is what is known and can be controlled, including human actions (interventions, impacts, activities, incentives, regulation, policy—and, among stakeholders, acceptance of that policy), while the real world remains unknown except for the observations that are made of it. These observations may be perceptions/perspectives, monitoring of important aspects of the human and natural systems relevant for management, or developments in understanding of these systems. The intersection of the management and real worlds are through human actions and observations.

The relationships of different subsystems in both worlds are illustrated using a digraph methodology, where two subsystems ("nodes") are linked via an "edge" or interaction. In this example, the strength of the interaction relative to other interactions is indicated by the width of the line, and its certainty by the length of the dashes. An arrowhead or a circle indicates whether the interaction is a positive or negative correlation, i.e. if the magnitude of one subsystem or variable increases then the other will increase if the correlation is positive or decrease if it is negative, and vice versa. This relationship and the strength of interaction is the exposure. The size of the arrowhead or circle can be used to indicate vulnerability and its shade an indication of certainty. In framing the process for managing a climate-related risk, knowledge can be used to map such a digraph, with methods available to explore what might happen to all the nodes in the system if you "press" one or more nodes by a directional change—increase or decrease.

A mapping process such as this is useful, at least, during the "sense making" phase for helping decision-makers and stakeholders alike to better understand the nature of the problem and the degree of knowledge and uncertainty that need to be addressed for making robust decisions (Melbourne-Thomas et al., 2013). Not included in this illustration are the potential interactions with other human and natural subsystems or with managing other risks. These can be readily developed in such a diagram to explore and consider whether such interactions need to be addressed.

These questions may be explored with heuristic models, network (pathway) models, statistical models, dynamic mathematical models or a mixture of types, depending on the available knowledge and data. Some approaches to decision analysis are limited to specific types of models, while others are more flexible. The robustness of a model for decision making is determined by the degree to which an action will be systematically chosen for the task and correctly ameliorate risks as expected. **Box 2** illustrates the development of a model highlighting some connections of different parts of the management and Earth Systems in managing the risks of damage from flooding.

The second form of modeling related to the decision-makers' and stakeholders' beliefs, values and objectives. These are more subjective and do not allow empirical validation. Moreover, the modeling is not descriptive in the sense that beliefs, values and objectives exist fully and explicitly before the modeling process begins. Rather the process of elicitation helps the participants reflect on what they are truly seeking to achieve and constructs the detailed objectives for the analysis (Keeney, 1992; Lichtenstein and Slovic, 2006; French, 2021). This form of modeling is particularly focused on helping the participants move from System 1 Thinking toward System 2 Thinking as it generally introduces rationality conditions that help their values become more consistent. Such modeling is known as prescriptive rather than descriptive modeling. Comparing and deliberating on different prescriptive models may also be important in Social Deliberation if some stakeholders hold to dogma that conflicts with current established approaches. While good decision-making depends on sound empirical description of the context, the process of reaching a decision and consensual acceptance of the selected course of action are not necessarily helped by effectively informing some of the stakeholders that they are "simply wrong" (French and Argyris, 2018), so the deliberations around prescriptive models need to be carefully and sensitively facilitated.

There is much emphasis currently on evidence-based decision-making and we would certainly echo this, but with a careful interpretation. Evidence and the knowledge that it supports is often encoded in descriptive models. We only have direct observations about the past. Decision-making is about planning for the future and so to use observations, we must make judgements about its relevance to the future: do we believe that things will continue in this way or that? Moreover, in many cases relating to risk management, what evidence we have is partial, if indeed we have sufficient data to claim any validated evidence at all. This inevitably means that there is a tension between scientific advisors, who want more time to accumulate and validate evidence, and the decision-makers, who need to make urgent decisions to mitigate risks. Decision analysts need to appreciate this tension in managing the deliberations between decision makers, their scientific experts and stakeholders.

A tension exists between observations, evidence, models about the future and effective risk management related to climate change; what constitutes evidence in climate-related risk management? In the last three decades, the Drivers-Pressures-State change-Impact-Response (DPSIR) framework has grown to underpin evidence-based management (Patrício et al., 2016). At its heart, is the need to attribute change to a driving cause; attribution of climate change to greenhouse gas emmissions from human activity has been a central theme of the Intergovernmental Panel on Climate Change (Bindoff et al., 2013). The application of DPSIR is usually at small spatial scales (10,000 km^2 at most) (Patrício et al., 2016) with a view that impacts can be detected and, once detected, restoration would be possible within a similar time frame. Such an approach implies that failure to not have a significant impact can be easily detected

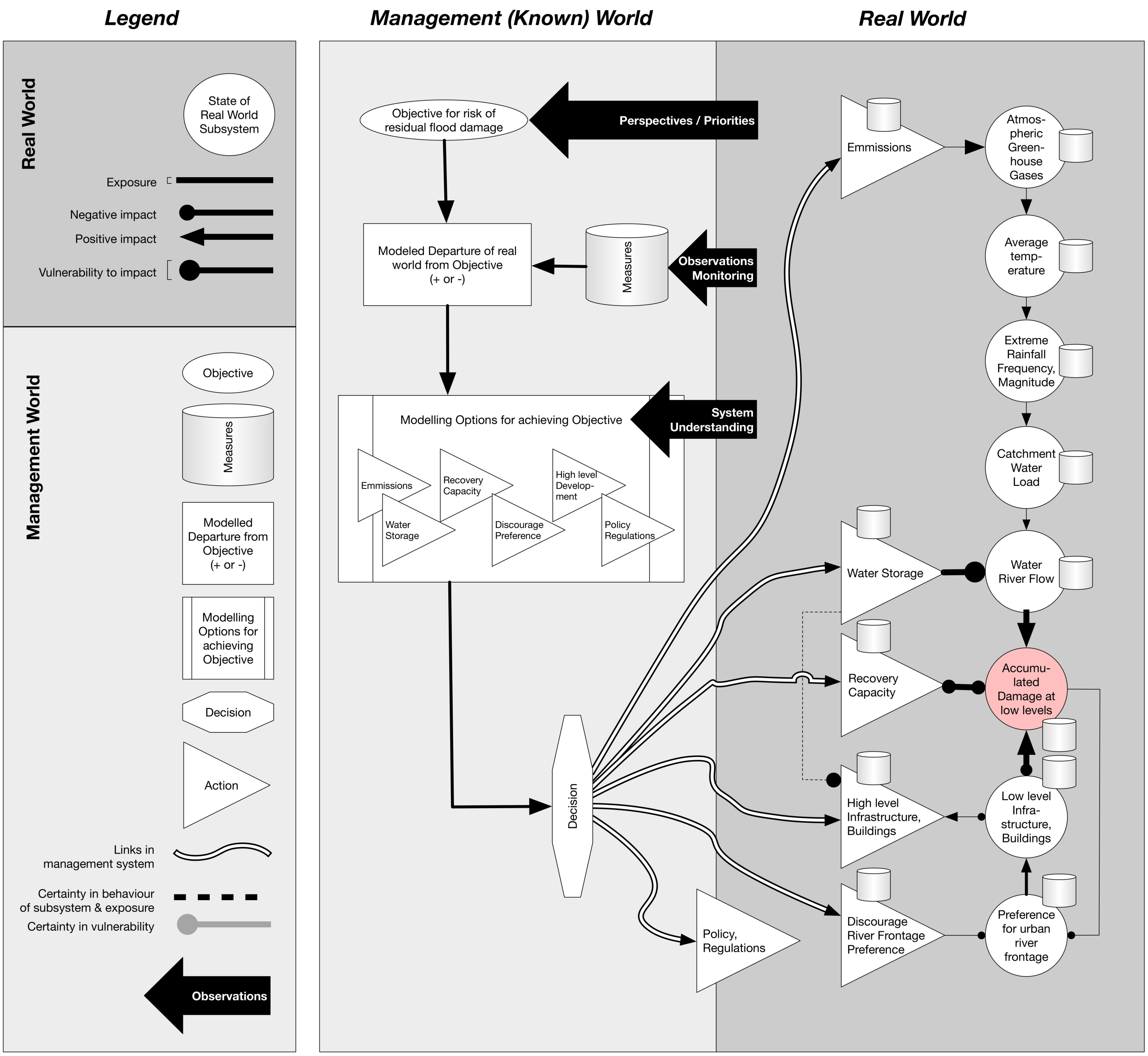

FIGURE 3 | Example system managing risk of accumulated damage (red circle) of low level areas prone to flooding in the real world (**Box 2**). Each of the subsystems in the real world have a dynamic affected by internal drivers as well as the external inputs and outputs from other subsystems. The relationships (edges) between subsystems (nodes) and their effects on each other are mapped using a digraph. An end of an edge has an arrow (positive relationship), circle (negative relationship) or neither (no relationship), which indicates how the abutting subsystem will change when the subsystem at the other end of the edge changes. A positive relationship means the affected subsystem will change in the same direction as the impacting subsystem, and a negative relationship means the affected subsystem will change in the opposite direction. These subsystems may also be influenced by other Earth subsystems, human activities and/or management systems not illustrated here. Knowledge of the real world is constrained to the three black arrows. Interventions of the management system in the real world are through actions, which may in themselves be subsystems.

and rectified. In climate change, this is equivalent to accepting that an overshoot of a target global mean temperature would not be a disaster and that the climate can be restored before disastrous effects would arise. Yet, we know that the effects of greenhouse gases emitted now will take many decades before their effects will be diminished. Managing this risk requires decisions on actions well in advance of observations demonstrating impacts. Timeliness for action in risk management is an important factor not usually associated with DPSIR analyses. Uncertainty in both descriptive and prescriptive modeling increases the risks of failure. Evidence, therefore, needs to comprise not only observations of the state of the system but consider their power for detecting change and attributing it to the causes, as well as the degree to which models can help manage future risks.

Lastly, we are aware that the prescriptive modeling and analysis used to support decision-making can be interpreted naively as algorithmic computations on simple, often linear models without concern for the wider processes that these calculations support. To be frank, one of us has seen many naïve analyses performed by quantitatively adept scientists which have not truly supported the socio-political processes that surround any complex decision and which consequently have not really informed the decision-makers and stakeholders. Effective decision analysis uses the prescriptive modeling to articulate the deliberations between the participants building a shared understanding of the issues and each other's perceptions and values. It is through that shared understanding that a decision emerges, not simply from the maximization of some objective function. So in the next sections we emphasize many such "softer" socio-political issues that need to be reflected upon and brought into the deliberations in developing appropriate decision analyses for a set of issues.

Contextual Issues

Decisions are affected by many contextual factors beyond the formality and constraints of the processes used (see French and Geldermann, 2005; Hodgkinson and Starbuck, 2008; French et al., 2009 for a wider discussion of contextual issues) and can be explicitly incorporated in the analyses leading to and supporting decisions. Some important issues to consider are:

- The "**decision-maker**" may be an individual, a group sharing responsibility, a community, an organization or other legal entity, a government or, in some senses, by society itself.
- The degree of "**system understanding**" of the risk to be managed, including the root causes and drivers of the risk (cause and effect), and the way the risk and its consequent effects manifest and encoded by the descriptive model of the system.
- The **range of possible options** for managing risk may vary between a few alternatives and effectively an infinite number.
- There can be many **other players involved**: stakeholders who will share in the potential impacts in diverse ways; experts who can advise on possible actions, other risks and consequences; and the decision analysts who develop the decision modeling and use this to help articulate deliberation.
- **Culture** is an important element, especially in relation to the recognition of subjectivity in the discussions and whether this should be modeled and made explicit. Stakeholders' response to risk and uncertainty has many cultural influences (Hofstede, 1984; Thompson et al., 1990; Douglas, 1992). Since climate change is a global issue, variation in local culture can mean that a decision tool and approach appropriate to a set of issues in one region may be inappropriate for seemingly the same issues in another.
- The **time and other resources available** before a decision must be made can constrain the range of investigations and modeling used.
- The range and depth of **uncertainties** involved are very important (see Subsection Types of Uncertainties).
- The **values and objectives driving the decision** may differ between options too. In the private sector, the profit motive and shareholder value may not override other criteria, but financial objectives have high weight; whereas the public sector have more altruistic objectives reflecting responsibilities to, e.g., the public, maintaining society and the environment (see Subsection Values and Objectives).

Box 2 develops these concepts as part of a control system, using a simplified example of managing the risks associated with flooding based on a model of how the management and Earth system might work. The contextual issues that arise in mitigating and adapting to climate change are important in determining suitable decision processes and tools. Firstly, the threatened impacts are global, but with many regional and continental differences in the scale and type of impact. Different areas of societal and business activity will be affected differently. A wide range of stakeholder interests will need to be considered in almost all cases, including those of humanity itself. There are ethical and moral issues to consider alongside more prosaic objectives. The breadth of uncertainties, many of which are deep and difficult to assess, is huge. While less so than in previous decades, climate science is controversial, and consensus will be hard to achieve across all stakeholders.

Types of Uncertainties

Situations of Uncertainty

The breadth of uncertainties can be overwhelming. Courses of action are broadly constrained by the knowledge readily available and the familiarity present in a situation. Identifying the general situation with respect to uncertainty will direct DM planning from the beginning and facilitate communication on what is required.

Cynefin is a way of categorizing decision contexts ("spaces") according to the decision-makers' and their experts' knowledge of cause and effect and hence their ability to model the system (Snowden, 2002; French, 2013) (see also the community of practice—https://www.cognitive-edge.com/). If a context is known or knowable, then it will be possible usually to build sophisticated models and make sound predictions; but if the context is complex and chaotic only the simplest of models will be possible. Courtney (2003) and others have characterized uncertainty simply on the quality and precision of models that can be built and developed, a very similar categorization to *Cynefin*. We have chosen to go with the *Cynefin* formalism since it seems clearer to us to think of knowledge of cause and effect in general terms, rather than when knowledge is specifically expressed as a formal model.

Cynefin recognizes four broad cases (**Figure 4**):

Known contexts, in which the only uncertainties relate to stochastic effects, i.e. randomness; cause and effect are broadly understood to within natural variation and randomness.

Knowable contexts, in which one has models and good scientific understanding, but there is a need for data to determine certain parameters.

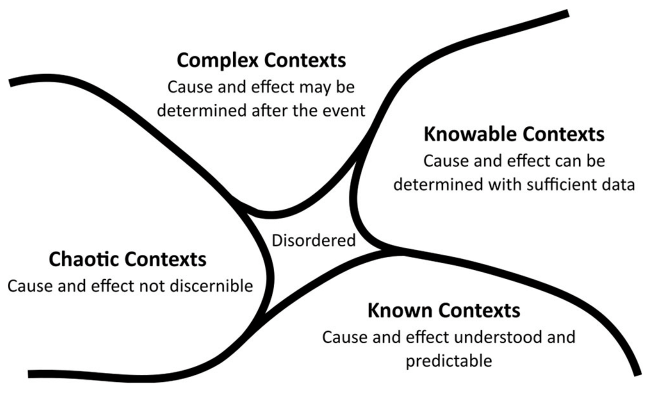

FIGURE 4 | Cynefin.

Complex contexts, in which there is considerable lack of knowledge. Causes and effects are known, but not precisely how they are related, making prediction of the consequences of a decision difficult and very uncertain. Uncertainties here may be deep.

Chaotic contexts, in which hardly anything is known; possible causes and effects are both unidentified.

There is a fifth area in **Figure 4**, relating to disordered contexts, i.e., those contexts which have yet to be classified. While disordered contexts may be important in other applications of *Cynefin*, one of the first tasks in problem formulation is to understand and classify the context so the disordered area quickly becomes irrelevant to decision analysis. Moving from the Chaotic Space through the Complex and Knowable Spaces to the Known Space, our knowledge and understanding move from deep uncertainty to certainty. Epistemology from sense-making through inference to full knowledge can be described very simply against the backdrop of *Cynefin* (French, 2013). Various decision analytic techniques are available for the Known, Knowable and Complex Spaces, but in the Chaotic Space decision-making is a matter of trial and error; or, if there is time, defer any decision and investigate the situation to see if one can learn enough to move the context into the Complex Space. An outcome of this approach is to provide greater openness as to the scale of the problem relative to the knowledge base, which then promotes more obvious courses of action.

Types of Uncertainty

Decision-makers can face many forms of uncertainty. Many typologies have been developed to describe these, each focusing on one or more characteristics (Knight, 1921; Berkeley and Humphreys, 1982; French, 1995b; Paté-Cornell, 1996; French et al., 2020). Discussions of uncertainties often focus on the external world within which the problem is being faced, and for which we describe three types of uncertainties—stochastic, epistemic (structural) and analytical. We also describe two important uncertainties internal to the decision process—ambiguity and values—relating to the decision-makers' and stakeholders' perceptions and valuations of the world. These five uncertainties are:

Stochastic: relating to physical randomness and natural variability. These are typically modeled with probability and simulations (Morgan, 2008).

Epistemic relating to a lack of knowledge or understanding about the external world and the mechanisms underpinning relevant phenomena. Epistemic uncertainty is addressed by statistical analysis, be it frequentist in which standard errors, *p*-values, confidence intervals etc. give some indication of its scale, or Bayesian in which epistemic uncertainty is fully modeled through probability (Jeffreys, 1961; Barnett, 1999; Christensen et al., 2011; Spiegelhalter, 2019).

Analytical relating to the approximations and model choices that are made in conducting an analysis. This form of uncertainty is often overlooked. Firstly, models are never full and true representation of reality; there is always modeling error. Secondly, computation is never without error and large-scale climate and environmental models have many approximations built into them and the algorithms used to do the calculations. Analytical uncertainties can be analyzed probabilistically, but often only bounds are used (Hennig et al., 2015).

Ambiguity relating to a lack of specificity in the description of some system or impact. Inevitably in deliberations about climate change among a plethora of stakeholders, terminology is not used in unique ways and ambiguities and imprecision arise leading to uncertainty. This is not a form of uncertainty that should be modeled. Rather it should be resolved by discussion and agreement on terms.

Value relating to a lack of clarity on how to value an impact. For instance, all the stakeholders and decision-makers concerned may agree that climate change adaption measure should ensure the sustainability of local agriculture, but be unclear about the precise meaning of this phrase. Again there is no benefit in modeling such uncertainties. They need to be resolved by discussion and agreement (Keeney, 1992; French, 1995b; French et al., 2020).

Decision tools and processes can address all five uncertainties, though many concentrate on just one or two. For instance, confining attention to ambiguity and value uncertainties and ignoring stochastic and epistemic uncertainties can help focus discussion sufficiently to clarify goals and objectives and support deliberation between wider stakeholder groups and decision-makers. Partitioning and classifying the components of any uncertainty into these five wide categories is a matter of judgement; but the process of doing so catalyses discussion and helps ensure that all uncertainties are noted in any analysis,

TABLE 2 | Types of uncertainty that can arise in different aspects of an analysis supporting a decision on mitigation or adaption.

		Type of Uncertainty				
		Stochastic	**Epistemic**	**Analytical**	**Ambiguities**	**Value**
Aspects of a decision	Nature of the hazard	Frequency	Magnitude	Model and computational accuracy	Interpretation of goals and objectives	
	Consequences of the hazard	Variable outcomes of mechanisms	Pathways; Mechanisms; Other human causes	Model and computational accuracy		Importance of potential consequences
	Net effects of adaptation actions	Variable outcomes of mechanisms	Pathways; Mechanisms	Model and computational accuracy		
	Time until hazard of concern	Variability giving rise to conditions of concern	Magnitude	Model and computational accuracy		
	Implementation of actions	Implementation errors; project delays	Funding mechanisms		Obligation; compliance	Importance of action relative to other activities
	Correction and/or further adaptation	Variable outcomes of mechanisms	Pathways; mechanisms correct identification of need	Model and computational accuracy	Understanding of need	Importance of potential consequences; Importance of action relative to other activities
	Responsibility to make decision	Attitudes of decision-maker	Legal, economic and social frameworks		Responsibility Interpretation of the law	
	Scope of action		Natural boundaries of effects of action		Scale of jurisdiction	

even if some are subsequently ignored in order to focus on others.

Any of these uncertainties can be too deep to be modeled and analyzed or resolved by deliberation within the time and resources available for a decision. This may happen because data are very sparse, expert disagreements very wide or, in the case of value uncertainties, ethical issues extremely complex and controversial. In such cases, however the uncertainties should be dealt with *in principle*; the depth of disagreement between experts and stakeholders, the lack of data, and the need to make a decision relatively quickly mean that in practice methods that can deal with deep uncertainties will need to be adopted until the uncertainties can be resolved (Walker et al., 2013; Marchau et al., 2019; French, 2020). We discuss this further below.

Table 2 helps relates these different types of uncertainties to some of the challenges that arise in facing up to a climate change issue. For instance, consider specific hazards (row 2). Uncertainties may concern (i) the frequency with which an extreme weather condition occurs; (ii) how large a change in the weather extremes will occur; (iii) how well we can predict the weather pattern; (iv) what the goals and objectives would be in adapting to the new pattern and (v) how serious the effects would be in terms of these goals and objectives.

Uncertainty does not just relate to what might happen (i.e. stochastic, epistemic and analytical uncertainties); but also to how well potential impacts can be described and valued (i.e. ambiguity and value uncertainties). This can be true at organizational and governmental levels as much as for individuals; and may be particularly the case when the scale of an issue in space or time is large, as is usual in climate change contexts. Issues that extend over regions or countries or over long timespans have strong tendencies to be set in complex socio-political and economic contexts in which values are uncertain and hotly debated, making them complex or even chaotic contexts for decision-making, however straightforward a technical solution might seem.

The balance between how particular decision analyses address uncertainties relating to the external world and those relating to the values driving the decision making is important. Some analyses partially ignore uncertainties relating to the former in order to focus on conflicts in the values held by different stakeholders and help structure debate; others build very sophisticated models of the external world to predict potential consequences, but in doing so lose transparency and risk becoming untrustworthy black boxes to many stakeholders. There are no methods which guarantee to balance such conflicts and provide a oath through such complexities, but skilled decision analysts have the professional facilitation skills that can help find a resolution (Phillips, 2007; French et al., 2009).

Values and Objectives

Decision making is driven by values, by what the decision-makers want to achieve. Values are necessarily subjective, but in societies that seek to avoid explicit subjectivity in their decision-making, economics and financial theory provide ways of costing many climate change impacts in a broadly objective manner; but there are some "intangible" impacts such as the loss of a historic site or natural estate, or the cultural impact of moving communities that are difficult to cost. The ability to assess intangible impacts, albeit subjectively, is one of the characteristics that distinguish different schools of decision analysis.

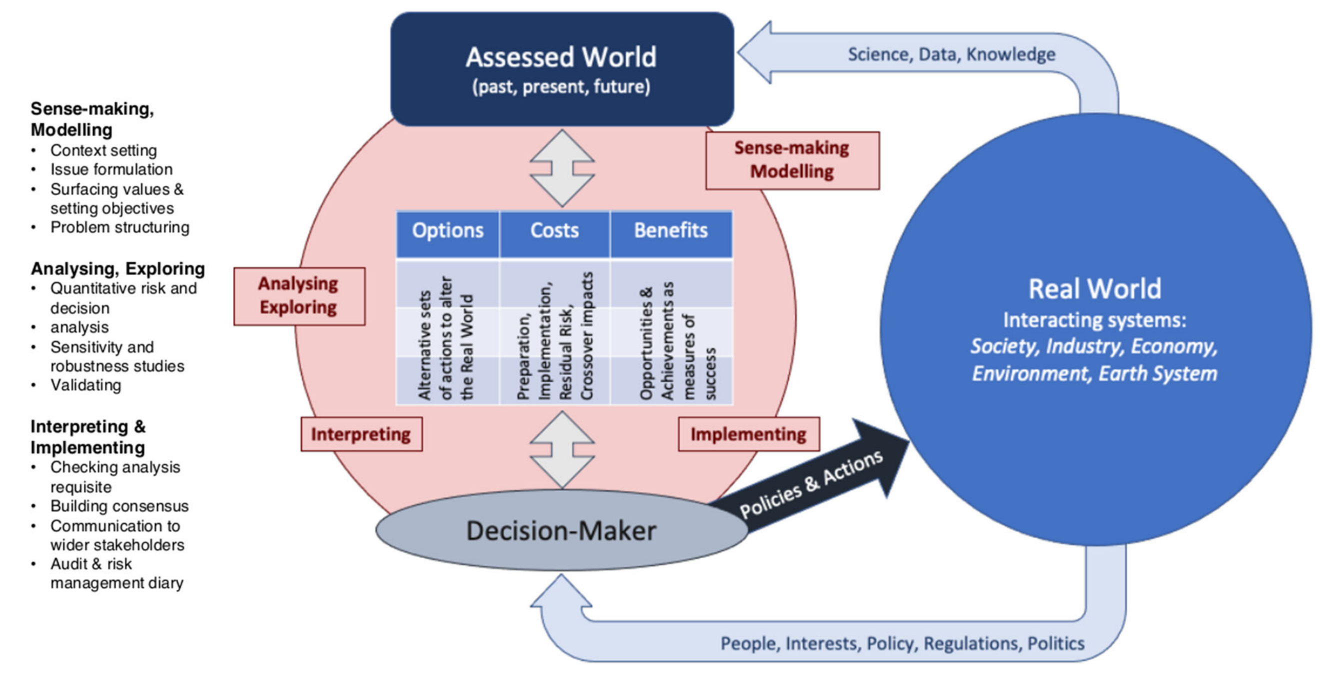

FIGURE 5 | Setting the three decision making phases into a wider context of a control system. The **left-hand side** of the graphic corresponds with the human processes of conceptualizing, modeling, analyzing and deliberating on the issues; the **right-hand side** to the real world and society. In a well-developed simple control system, the "Science, Data, and Knowledge" are measurements (feedbacks, monitoring) of the real world, the "sense making" will have been previously simplified to one or more target objectives, the "analysis and exploration" process is simplified to estimating the difference between the state of the system and the target/desired state, and the "interpretation and implementation" process is simplified to pre-agreed actions to move the system from its current state to the target state.

Although we have discussed contextual issues and uncertainties first, good decision making in practice follows value-focused thinking. Keeney (1992) describes this as "first deciding what you want then figuring out how to get it." This runs counter to the more usual alternative-focused approach: namely first identifying some alternatives, then deciding between them. However, value-focused decision making is more creative, not being confined to a set of pre-defined alternatives. Moreover, being aware of the objectives of a decision analysis at the outset means that analytic effort can be focused on what matters, avoiding irrelevancies and providing the means by which any options can be evaluated for their contribution to a solution. In particular, since climate change, environmental and economic models can be very computationally expensive to analyse, value-focused thinking can direct effort to calculating what matters; the scale of the effort required to address the problem can be more easily identified.

Economic and financial methods provide one way of exploring values and objectives: e.g. cost-benefit methods seek for each alternative to evaluate the total cost of implementation and consider it relative to the cost of potential impacts that the alternative ameliorates (Boardman et al., 2017; OECD, 2018). More generally, value and utility methods offer ways of assessing both tangible and intangible costs and benefits, albeit relying more of subjective or, at least, less objective inputs (Keeney, 1992; Keeney and Raiffa, 1993; Bedford et al., 2005).

In passing, we note that many perspectives on rational decision-making separate the Science from the Values that need to be balanced in making a choice. By "Science" we mean the knowledge and investigations that can be brought to bear on resolving the issue and addressing the uncertainties. By "Values", we mean the decision-makers' objectives that the ultimate choice seeks to meet. Of course, in any democratic society addressing climate change issues, the decision-makers should draw stakeholders' objectives into the ones that they use in the analysis (Renn, 2008; Rios Insua and French, 2010).

THE DECISION-MAKING PROCESS

In control systems, a decision process will have in mind to update the controls in a regular feedback process. Simple control systems will have only one control with a pre-determined target for adjusting the control based on a measurement of the state of the system – as in the thermostat in our example. More diffuse controllers such as for the climate system, may use many different actions including new actions as differences between the state of the system and the target are measured, considered and responded to. If a risk has only been identified for the first time, then part of the decision process in this first instance will be to determine not only the actions to ameliorate the risk but also whether, and when, to assess in the future the success, failure or other impacts of the actions and whether subsequent adjustments or new actions are needed.

Phases

Almost every writer on decision analysis has summarized the decision-making process as a cyclic iteration of several phases (see the many citations to decision analysis in this paper). Here we use three broad phases, which are adequate for our purposes:

Sense-Making and Modeling: Before any auditable, rational decision-making can begin, it is necessary to identify issues, values, objectives, uncertainties, stakeholders, possible actions and their consequences, engage with stakeholders and consult experts as needed, and determine the scope and boundaries of the subsequent analyses. Only when substantial progress has been made on these, is it possible to build a quantitative model and conduct any analysis. This is also a time when the interaction between different risks and decision processes can be mapped, the relative importance of each identified, and the need for integration in their ongoing management.

Analyzing and Exploring: Once a model is built and/or appropriate existing data and knowledge services are identified, exploration and analyses are undertaken in relation to the study's objectives, options and generally building an understanding. Sensitivity and robustness analyses may – should – supplement the decision analysis, setting bounds on some of the residual uncertainty. During the process, the model and information should be validated as much as possible against available data and the decision-makers', experts' and stakeholders' perceptions. The detail and application of this phase is very much dependent on the *Cynefin* context in which the problem starts out, and, if needed, how much time may be available to move the problem from one context to the next.

Interpreting and Implementing: The results and guidance offered by the analysis need to be interpreted into real world actions. This requires that the decision-makers and analysts make a judgement whether the analysis is adequate or, in technical terminology, *requisite* for the decision, guiding them to a consensus on the way forward (French et al., 2009). They need to judge whether the model, the analysis and the conclusions are fit for their purposes. Once made, they will also need to communicate the decision to stakeholders and implement the actions.

Figure 5 relates the three phases to the use of data from the real world, and choosing from available options to meet the policy objectives. The left-hand side of the graphic corresponds to the discussions, deliberations, analyses and studies that support the decision making. The right-hand side relates to the real world, which is always too complex to be perfectly modeled or analyzed. We emphasize that the real world includes not just relevant changes in climate, but human society, the environment, business, industry and agriculture and all the systems that need be considered in developing policies in mitigation and adaption.

Generally, the three phases of decision-making proceed from the top to the bottom of the graphic and are indicated by the bulleted lists, but we recognize that analyses, discussions and deliberation will iterate backwords and forwards as understanding of the issue grows. The "decision-maker" at the bottom of the graphic is to be understood as the person or, more likely, group, who are responsible and accountable for the decision under the appropriate governance structure. We emphasize that the interactions of this decision-maker with the real world include appropriate consultations and engagement with stakeholders.

This apparently linear approach from problem to decision implies risk management is organized, that all risks are identified and the processes set in train are carried out with some order, including the monitoring of success. Yet this is obviously rarely the case. Invariably, the process iterates within and between phases as thinking about one issue catalyses further thoughts about other issues or reflections during one phase indicate that other issues should have been considered in an earlier one. Further, problems may be latent, arising at seemingly random times, decisions postponed, and attention of scarce resources diverted to other purposes some way during the process. Moreover, many risks will be interrelated, and will be dealt with on differing timelines and urgencies. Being mindful of these relationships between risks and between their management process can help reduce tensions between them, take advantage of synergies in activities and processes, and avoid inadvertent negative consequences between risks.

Simplistically, decision analytic studies tend to be conducted in one of two modes (Franco and Montibeller, 2010).

- The *expert* mode in which the analysts work away from the decision-makers, experts and stakeholders, consulting them individually or groups as necessary to gather information. Such studies are common in addressing problems in the *Cynefin* Known and Knowable spaces. Because such problems occur commonly, well-structured models are relatively easy to build. The analysts' task is mainly to run sophisticated computer codes to explore and analyse the system.
- The *facilitated modeling* mode in which analysts and decision-makers, accompanied maybe by some experts and stakeholders, meet in one or more workshops to "solve" the problem. Such studies are common in tackling contexts lying in the *Cynefin* Complex and Chaotic spaces. Initially the emphasis is on understanding the perceptions of the group on what is happening and identifying possible strategies that may be taken up in response, and on the values that will drive their decision-making. Later, quantitative models are built in the presence of the group to capture these and numerical inputs elicited for those quantities that cannot be inferred from "objective" data. The group see and explore the analysis together, before deciding on a course of action.

This rough dichotomy is an oversimplification; many studies involve elements of both. Large projects dealing with complex issues, and integrating across related risks, may begin with several facilitated workshops to explore and identify issues, creating a series of questions. These questions are then explored through sophisticated modeling studies carried out in the expert mode. Later, there may be a return to facilitated modeling to share what has been learnt and evaluate possible strategies, providing guidance to the decision-makers. Some or all of the workshops might be conducted as face-to-face events or remotely (Coakes et al., 2002; French et al., 2009; Nunamaker et al., 2014; Pyrko et al., 2019).

Approaches to Decision Analysis

Decision analyses comprise many families of techniques, some with sufficient philosophical and methodological underpinnings to be called a "school"; while others are more collections of techniques with enough common qualities to be grouped together. We have categorized seven broad classes of techniques that support decision making and give details of each approach in **Table 3**, identifying how they relate to the general considerations in our earlier discussion.

Bayesian Methods

Bayesian methods provide a structured approach to assembling information around the consequences of choices, either by modeling, analysis of multiple scenarios or structuring deliberation. They can address all types of uncertainties, and are underpinned by axiomatic theoretical bases and powerful computational methods. These most assuredly form a school built on a coherent set of assumptions and philosophical perspectives. Methods can draw in both hard data and expert knowledge weighing them together appropriately. They use the same Bayesian statistical approaches that lie at the heart of many machine learning and artificial intelligence algorithms. Intuitive, graphical interfaces such as decision trees, belief nets and influence diagrams make the methods relatively transparent. Bayesian methods emphasize the auditable, building of consensus. They make explicit the biases (subjectivity) of information, stakeholders and the decision-maker. Traditionally, Bayesian methods use probability to represent uncertainty, multi-attribute utility functions to represent preference and then maximize expected utility to identify an "optimal" decision. As such they apply in the Known and Knowable Spaces. However, the use of multiple scenarios, sensitivity analysis and exploratory decision conferences enable the methods to be applied in the Complex Space (Keeney and Raiffa, 1993; French and Rios Insua, 2000; Smith, 2010; Howard and Abbas, 2016; French, 2020; Workman et al., 2021) (See **Table 3a** for further details).

Decision-Making Under Deep Uncertainty

Deep uncertainty relates to circumstances in which data are too sparse, experts in too much disagreement or time is too short to model the uncertainty. As such, decision-making under deep uncertainty (DMDU) methods are focused on working in the Complex Space. Approaches here emphasize robustness ("no regrets" options) and the use of scenarios, and often link well with scenario-focused robust Bayesian studies. Indeed, DMDU studies draw in many other approaches to decision analysis, using them to identify robust rather than optimal strategies. DMDU analyses can help decision makers to think contingently and build a more wide-ranging recognition of the risks (Walker et al., 2013; Maier et al., 2016; Marchau et al., 2019; French, 2020; Workman et al., 2021) (See **Table 3b** for further details).

Decision Process and Risk Management Tools

The process of decision-making can be very complex, extending over time and involving many parties. A range of tools and techniques have grown up to help manage the decision-making process and support risk management and the implementation of the chosen strategy. Some tools organize data and analyses, often being built on a geographic information system. Others manage processes, organizing workflows. Some have inevitably expanded in function to support decision-making itself, even though their primary focus might be on, say, implementation and monitoring risks. They apply in all the Cynefin Spaces. Such tools are closely related to knowledge management systems; knowledge management processes and decision process management differ more in terminology than in substance (Dalkir, 2005; French et al., 2009; Jashapara, 2011) (See **Table 3c** for further details).

Economic and Financial Approaches

Many of the tools involved in analyzing decisions stem from economic theory and accounting practices: e.g., cost benefit analysis, which seeks to price out all aspects of the consequence of a strategy, or real options theory, which seeks to value financial investments allowing for their risks and the contingent buying and selling. Such methods are perceived as objective when dealing with tangibles, but are more controversial in their valuing of intangibles. Since these methods model uncertainties with probabilities and then work with expectations, they share much in common with Bayesian methods. However, many applications of cost-benefit analysis omit any detailed treatment of uncertainty. Because of the detailed data requirements of these methods, their application is limited to the Known and Knowable Spaces, though there have been some investigations of using real options in the face of deep uncertainty (Neely and de Neufville, 2001; Bedford et al., 2005; Pearce et al., 2006; Hallegatte et al., 2013; Buurman and Babovic, 2016; Boardman et al., 2017) (See **Table 3d** for further details).

Interval Methods

Because of concerns that the statistical accuracy of some data is unknown and that decision-makers and experts cannot make numerical judgements accurately, analyses have been suggested which accept ranges for numerical inputs. While avoiding accuracy issues, weakening the arithmetic also may weaken other foundational assumptions, including some basic principles of rationality. Different types of uncertainty can often be confused, and the analyses can contradict basic probability theory. Interval models of semantic, and imprecision can be useful in exploring ambiguity and value uncertainty, though modeling rather than resolving such uncertainties does not necessary help in decision-making. Some interval methods can be thought of more as sensitivity techniques applied to other decision analytic approaches. Typical approaches here relate to the fuzzy or possibility theory, and evidential reasoning. Interval methods can be applied in the Known, Knowable and Complex

TABLE 3 | Characteristics of the main approaches to decision analysis with respect to their Cynefin context, the manner in which they can be used to address different uncertainties, where they may be used in different phases of the decision-making process, the resources required, and some case studies for further exploring how they might be used.

(a) Bayesian Methods (Keeney and Raiffa, 1993; Smith, 2010; Gelman et al., 2013; Reilly and Clemen, 2013; Howard and Abbas, 2016; Marchau et al., 2019)

Uncertainties		***Cynefin***			
Stochastic, epistemic, analytical	**Ambiguity, Value**	**Known**	**Knowable**	**Complex**	**Chaotic**
All can be modeled probabilistically, perhaps supplemented by sensitivity analysis (Rios Insua, 1999; Rios Insua and Ruggeri, 2000; Iooss and Saltelli, 2017). Deep uncertainties can be investigated via scenarios (French, 2020).	Uncertainties resolved or reduced by discussion, then values modeled by multi-attribute values and utilities (Keeney, 1992; Keeney and Raiffa, 1993; Gregory et al., 2012). Residual uncertainties explored via sensitivity analysis.	Any stochastic uncertainties modeled probabilistically; otherwise, deterministic modeling with sensitivity analysis. Value functions tend to be used more than utility functions (Keeney and Raiffa, 1993; Goodwin and Wright, 2014).	Epistemic uncertainties updated via Bayesian statistics/machine learning, then remaining stochastic uncertainties modeled probabilistically. Full Bayesian decision modeling possible (French et al., 2009; Smith, 2010; Howard and Abbas, 2016).	More exploratory analysis (Gelman, 2003) to understand behaviors with less complex Bayesian modeling support by sensitivity and robustness studies. (Rios Insua, 1990; French, 2003) Scenario focused decision analysis to cope with deep uncertainties (French, 2020). Careful deliberations to construct values and utilities (Keeney and Raiffa, 1993; Gregory et al., 2012).	Formal modeling impossible. Much exploratory work to identify potential causes and effects. Little if any complex analysis.

Decision making process			**Resources required**	**Case studies**
Sense-making and modeling	**Analyzing and exploring**	**Interpreting and implementing**		
Construction of hierarchical models, belief nets (Sperotto et al., 2017; Phan et al., 2019), decision trees (Keeney and Raiffa, 1993) and influence diagrams (Keeney and Raiffa, 1993; Reilly and Clemen, 2013), supplemented by many soft elicitation techniques help build models for quantitative analysis (Gelman, 2003; Bendoly and Clark, 2016).	Bayesian updating and expected utility analysis, supplemented by robustness and sensitivity analyses (Rios Insua, 1999; Rios Insua and Ruggeri, 2000; French et al., 2009; Smith, 2010; Reilly and Clemen, 2013; Howard and Abbas, 2016)	Use of graphical models and sensitivity plots can help explain reasoning for strategy to stakeholders and implementers (Bendoly and Clark, 2016).	Bayesian decision analytic models can be applied with increasing complexity and sophistication to any given problem. Coherence between different levels of sophistication can be maintained. Thus the resources can be tailored to the time and support available for the analysis. The most sophisticated analyses are computationally demanding.	Baker and Solak, 2011; Catenacci and Giupponi, 2013; Richards et al., 2013, 2016; Åström et al., 2014; Alexeeff et al., 2016; Sperotto et al., 2017, 2019; Jäger et al., 2018; Phan et al., 2019

(Continued)

TABLE 3 | Continued

(b) Decision-making under deep uncertainty (DMDU) (Hallegatte et al., 2013; Weaver et al., 2013; Marchau et al., 2019)

Uncertainties		Cynefin			
Stochastic, epistemic, analytical	**Ambiguity, value**	**Known**	**Knowable**	**Complex**	**Chaotic**
Methods are designed for deep epistemic uncertainties. Some can deal with stochastic uncertainties. Analytical uncertainties seldom accounted for.	Some DMDU methods draw on MCDA methods and thus consider ambiguity and value uncertainties. In any case, DMDU methods support wide deliberation with stakeholders.	Not applicable because deep uncertainty is absent	Not applicable because deep uncertainty is absent	The complex and chaotic spaces are home to deep uncertainties. DMDU tools and more particularly processes are relevant here. The emphasis on robustness is very relevant. The tools themselves are relatively simply structured but are effective at stimulating discussion.	Deep uncertainties are rife in the chaotic contexts. DMDU emphases on robustness and possible scenarios can stimulate creative discussions of ill understood issues.

Decision making process			Resources required	Case studies
Sense-making and modeling	**Analyzing and exploring**	**Interpreting and implementing**		
Some of the simpler DMDU tools complement soft elicitation tools and can help to identify relevant scenarios and help formulate problems.	Many Bayesian or MCDA tools can be used here but with DMDU's additional emphasis on robustness and the exploration of several/many scenarios.	DMDU with its emphasis on robustness encourages contingency planning in implementation with careful monitoring to identify emerging risks.	Some of the simpler models do not require substantial resources, but the application of parallel sophisticated analyses in several scenarios can be computationally demanding. Also the emphasis on discussion of robustness can be demanding on the time of problem-owners, experts and stakeholders.	Lempert and Groves, 2010; Hall et al., 2012; Weaver et al., 2013; Taner et al., 2017; Brown et al., 2019; Groves et al., 2019; Workman et al., 2021

(Continued)

TABLE 3 | Continued

(c) Decision process management (Raz and Michael, 2001; Dalkir, 2005; Burstein and Holsapple, 2008; Jashapara, 2011; Bonczek et al., 2014; Sauter, 2014; Holsapple et al., 2019)

Uncertainties		**Cynefin**			
Stochastic, epistemic, analytical	**Ambiguity, value**	**Known**	**Knowable**	**Complex**	**Chaotic**
Not designed to address uncertainties involved in the decision itself, but may handle project risks in the decision process, especially implementation.	Not usually addressed, since ambiguities and value uncertainties will be addressed in the decision making itself, but may use those values in risk management of implementation.	Simple project management tools may be sufficient here.	Project management and risk management tools apply easily here.	Project management and risk management tools may be used but attention needs to be paid to risks that are complex in nature with little knowledge of precise relationships between cause and effects.	Project management and risk management tools may be used but attention needs to be paid to risks that are complex in nature with little knowledge of precise relationships between cause and effects.

Decision making process			**Resources required**	**Case studies**
Sense-making and modeling	**Analyzing and exploring**	**Interpreting and implementing**		
Process, project, knowledge elicitation and risk management tools help identify how to structure decision-making process. Decision process tools can capture details for implementation and document process for audit trail.	Tools help structure decision-making process and ensure timely involvement of problem owners, stakeholders and experts. Knowledge management tools can capture details for implementation and document process for audit trail.	Project management tools plan implementation and risk management tools identify what to monitor during implementation. Knowledge management tools maintain audit trail and track reasoning for choices made during implementation	Decision process management tools can reduce resources needed in the decision-making process. However, this assumes that the tools are already installed on local information systems and that the analysis team is experienced in using them. Otherwise, resource is needed to understand and train in the use of the tools.	Park et al., 2012; Papathanasiou et al., 2016; Biehl et al., 2017; Parding et al., 2020

(Continued)

TABLE 3 | Continued

(d) Economic and financial methods (Howell et al., 2001; Pearce et al., 2006; Boardman et al., 2017; Atkinson et al., 2018)

Uncertainties		Cynefin			
Stochastic, epistemic, analytical	**Ambiguity, value**	**Known**	**Knowable**	**Complex**	**Chaotic**
Cost-benefit methods usually deal with uncertainty via expectations with little attention to probability distributions; real options methods tend to treat uncertainty in much more sophisticated ways. Both methods, when applied fully have many points of contact with Bayesian methods (Neely and de Neufville, 2001; Bedford et al., 2005)	These methods reduce all value and preference information to financial equivalents. The key issues is to find a market in which all outcomes may be valued financially. Modern CBA methods use much more subtle techniques for this than those applied in the last century (Bedford et al., 2005; Saarikoski et al., 2016).	Although CBA and many financial methods work in theory, the complexity makes it seldom worth the effort.	The methods may be applied to evaluate complex projects but CBA tends to "average out" rather than analyse uncertainty.	The recognition of the need to treat deep uncertainties using real options has been investigated (Hallegatte et al., 2013; Buurman and Babovic, 2016)	Formal modeling impossible. Much exploratory work to identify potential causes and effects. Little if any complex analysis.

Decision making process			Resources required	Case studies
Sense-making and modeling	**Analyzing and exploring**	**Interpreting and implementing**		
In themselves, these methods do not support sense-making and modeling, though discussions of how to value impacts, both tangible and intangible can be catalytic in understanding the issues.	These tools focus mainly on analysis and evaluating the costs and benefits of various options. They are not designed to be used interactively so are more often deployed and communicated via reports than interactive workshops.	Since CBA methods do not emphasize the analysis of uncertainties and risks, they are less suited for use in developing and communicating an implementation plan. Real options with their emphasis on contingency are much more suited (Fischhoff, 2015).	Cost benefit analysis for complex projects is a major undertaking with much data collection needed to value outcomes. Real options also require data on risks and uncertainties. Both may have high computational needs.	Manocha and Babovic, 2017; de Ruig et al., 2019

(Continued)

TABLE 3 | Continued

(e) Interval methods (Shafer, 1976; Pedrycz et al., 2011)

Uncertainties		**Cynefin**			
Stochastic, epistemic, analytical	**Ambiguity, value**	**Known**	**Knowable**	**Complex**	**Chaotic**
There are issues of operational definition of quantities in some methodologies. Some simpler interval methods have no concept of conditionality so cannot model learning effectively, but there are some very sophisticated theories of evidence that can. Interval methods can also provide sensitivity analyses for Bayesian and MCDA methods (Shafer, 1976; Rios Insua, 1990)	Some methods can be simplistic with quantities not being operationally defined. The evidential reasoning approach to MCDA allows exploration of the relative weights on different criteria or between levels in criteria (Xu, 2012; Zhang et al., 2017)	Methods can be applied here without major issue, possibly because the simple, repetitive nature of the problem allows access to much data and the possibility of tuning the methods to the application.	Since the methods often capture rather than explore and resolve ambiguity and value uncertainties, they can hide issues. Also the lack, in some cases, of operational definitions may mean that some quantification is dubious. Evidential reasoning methods can help analyse conflicting objectives (French, 1995b; Xu, 2012)	The recognition of the need to treat deep uncertainties using real options has been investigated (Hallegatte et al., 2013; Buurman and Babovic, 2016)	The ability to deal with ambiguity may be helpful in poorly understood situations, but the emphasis on capturing ambiguity may ultimately slow the building of understanding.

Decision making process			**Resources required**	**Case studies**
Sense-making and modeling	**Analyzing and exploring**	**Interpreting and implementing**		
The emphasis on modeling ambiguity may help structure a model initially, but the lack of structures to model and explore complex interdependencies may inhibit the ability to build a valid representation of the issues.	If there is substantial data available then even the simplest of these methods can produce useful results. But with small quantities of data, their data analysis may be too inefficient. Evidential reasoning MCDA can be insightful on the preference side.	The emphasis on linguistic uncertainty may in some cases it may mask some of the issues. (French, 1995b)	Many methods are rather simple in application and require only moderate resources, but they may face issues in scaling up to major complex problems.	Gilbuena et al., 2013; Kim and Chung, 2013; Batisha, 2015; Yang et al., 2018

(Continued)

TABLE 3 | Continued

(f) Multi-criteria decision analysis (MCDA): full ranking and optimal seeking (Bell et al., 2001; Belton and Stewart, 2002; Bouyssou et al., 2006; Zopounidis and Pardalos, 2010; Tzeng and Huang, 2011; Velasquez and Hester, 2013; Kumar et al., 2017)

Uncertainties		Cynefin			
Stochastic, epistemic, analytical	**Ambiguity, value**	**Known**	**Knowable**	**Complex**	**Chaotic**
These methods tend to focus on balancing and resolving conflicting objectives and include little or no analysis of stochastic and epistemic uncertainties. Interactive methods that use complex objective functions do need to consider convergence criteria for analytic uncertainties.	Many methods here use multi-attribute value functions and focus on using weights to explore different emphases on conflicting objectives. One very popular method is AHP (Saaty, 1980), though this has issues in scaling up to evaluate more than a handful of policies.	Usually in the known context, the objective function is well understood; but in cases where it is not, interactive multi-objective programming can offer a way forward (Klamroth et al., 2018).	If the objective function is not well understood, then these methods can be useful and can be extended to stochastic programming, but epistemic uncertainties are not really addressed (Gutjahr and Pichler, 2016).	Methods can explore conflicting objectives, but seldom are able to address deep epistemic uncertainties, unless combined with scenarios (Stewart et al., 2013; Marchau et al., 2019; Durbach and Stewart, 2020).	Formal modeling impossible. Much exploratory work to identify potential causes and effects. Little if any complex analysis.

Decision making process			Resources required	Case studies
Sense-making and modeling	**Analyzing and exploring**	**Interpreting and implementing**		
There is growing experience in combining soft elicitation with tools to formulate problems (Marttunen et al., 2017). Many MCDA tools naturally encourage discussion and deliberation on developing appropriate value structures. However, exploration and formulation of stochastic and epistemological uncertainties is less developed (Durbach and Stewart, 2020)	Emphasis is usually on analyzing and exploring, resolving conflicting objectives. MCDA Methods come into their own at this stage of the process. Sensitivity tools and intuitive graphical displays exist for many of the methods (Gunawan and Azarm, 2005; Boardman et al., 2017).	Use of graphical models and sensitivity plots can help explain reasoning for strategy to stakeholders and implementers (Bendoly and Clark, 2016).	The more exploratory methods can be quite light in terms of computational resource, but require interactions with decision makers and stakeholders in workshops. Methods with use complex stochastic mathematical programming can be computationally demanding and require substantial data.	Konidari and Mavrakis, 2007; de Bruin et al., 2009; Streimikiene and Balezentis, 2013; Haque, 2016

(Continued)

TABLE 3 | Continued

(g) Multi-criteria decision analysis (MCDA): partial ranking (Roy, 1996; Bell et al., 2001; Belton and Stewart, 2002; Bouyssou et al., 2002, 2006; Behzadian et al., 2010; Zopounidis and Pardalos, 2010; Tzeng and Huang, 2011; De Smet and Lidouh, 2013; Velasquez and Hester, 2013; Figueira et al., 2016; Govindan and Jepsen, 2016)

Uncertainties		**Cynefin**			
Stochastic, epistemic, analytical	**Ambiguity, value**	**Known**	**Knowable**	**Complex**	**Chaotic**
Modeling of all forms of uncertainty including epistemic uncertainty is not the primary objective of these methods. Stochastic uncertainty may be included as probability distributions but there is no formalism for learning to address epistemic uncertainties. (Hyde et al., 2003; Behzadian et al., 2010; Gervásio and Da Silva, 2012)	Partial ranking or out ranking methods seek, first of all, to identify dominance between options and preference relations that can be agreed somewhat objectively. Thus first they eliminate suboptimal alternatives before seeking a fuller ranking. Ambiguity and value uncertainty may also be quantified (Behzadian et al., 2010; Figueira et al., 2016; Govindan and Jepsen, 2016).	Usually in the known context, the objective function is well understood; but when it is not, outranking methods can identify a partial ranking without need too many interactions with problem-owners.	Since epistemic uncertainties are not fully addressed, these methods can only help in relation to conflicting objectives, but robustness to uncertainties will need addressing (Hyde et al., 2003)	Outranking methods may be combined with scenarios to explore and analyse decisions under deep uncertainty. (Hyde et al., 2003; Durbach, 2014)	Formal modeling impossible. Much exploratory work to identify potential causes and effects. Little if any complex analysis.

Decision making process			**Resources required**	**Case studies**
Sense-making and modeling	**Analyzing and exploring**	**Interpreting and implementing**		
Graphical representations of partial orders are useful in model formulation, and the emphasis on exploring what can be said objectively about dominance relations can build a kernel of consensus between decision-makers and stakeholders.	ELECTRE and PROMETHEE implementations of outranking approaches have many tools for exploring partial relations and analyzing agreements and the reasoning behind these.	The analysis of dominance can provide a sound footing for building risk registers to aid implementation. Understanding the kernel of consensus can also aid communication.	If an outranking algorithm is essentially combinatorial in its approach then for complex problems there may be computational problems. Some of the methods may require less interaction with decision-makers and stakeholders if they can deduce many partial relations from objective data.	Markl-Hummel and Geldermann, 2014; El-Zein and Tonmoy, 2015; Xenarios and Polatidis, 2015; Michailidou et al., 2016

(Continued)

TABLE 3 | Continued

(h) Soft elicitation (Rosenhead and Mingers, 2001; Shaw et al., 2006, 2007; Ackermann, 2012; Bendoly and Clark, 2016)

Uncertainties		Cynefin			
Stochastic, epistemic, analytical	**Ambiguity, value**	**Known**	**Knowable**	**Complex**	**Chaotic**
Soft elicitation tools are available to elicit problem-owners' and experts' perceptions of these uncertainties and, more particularly, dependences and independences between them. Exploratory data analysis is also relevant (Steed et al., 2013; Bendoly and Clark, 2016).	There are tools to catalyse deliberations and help problem-owners and stakeholders clarify their meanings and contextualize their values to the specific issues being considered. (Keeney, 1992)	Usually problems falling into known contexts are well-understood and there is little need to elicit or structure models to perform analyses.	Problems falling into knowable space are usually well structured and problem owners' values are also well understood. However, there may be a need to explore error structures in preparation to estimate parameters in the models. (Gelman, 2003; Steed et al., 2013; Fekete and Primet, 2016)	Many soft elicitation tools were developed for complex contexts: 'wicked' problems with deep uncertainties: e.g., soft systems, cognitive maps and similar tools to elicit perceptions of relationships between entities and problem-owners' and stakeholder's values (Keeney, 1992; Rosenhead and Mingers, 2001)	Soft elicitation tools and processes can be use to catalyse creative thinking about poorly understood contexts.

Decision making process			Resources required	Case studies
Sense-making and modeling	**Analyzing and exploring**	**Interpreting and implementing**		
Soft elicitation tools provide much support to sense-making, formulating problems and identifying relevant issues to be addressed (Shaw et al., 2006, 2007; Ackermann, 2012)	Soft elicitation is not relevant to quantitative analysis and evaluation per se, but can support the exploration of residuals to understand the quality of the models and detect further factors to be addressed.	The results of soft elicitation provide the dimensions for communication by identifying the issues that are important to stakeholders and building understanding in those implementing the policies.	Physical resources requirements are relatively slight: sometimes post-its and a white board can be sufficient, though modern visual analytics can require substantial computing resource. However, the demands on the time of problem-owners, stakeholders and experts can be significant	Massingham, 2010; Butler et al., 2016; Bosomworth et al., 2017; Prober et al., 2017; Symstad et al., 2017

Spaces (Shafer, 1976; French, 1984, 1995a; Pedrycz et al., 2011; Xu, 2012) (See **Table 3e** for further details).

Multi-Criteria Decision Analysis

A term covering many approaches: indeed, Bayesian, DMDU and interval methods are sometimes considered multi-criteria decision analyses (MCDA). Some MCDA seek an optimal or best strategy; others form partial rankings, eliminating weak strategies but not discriminating fully between the better ones. Many MCDA methods eschew dealing with uncertainties and focus on modeling and exploring conflicting objectives and balancing these. Some methods have a rather pragmatic basis, although the European School of Multi-Criteria Decision Aid have much firmer philosophical foundations. There are MCDA methods that are appropriate to each of the Known, Knowable and Complex Spaces, though any method may be limited to just one of these spaces. MCDA techniques are especially useful in working with senior decision-makers in setting policy and broad objectives, and in processes of stakeholder engagement (Roy, 1996; Roy and Vanderpooten, 1996; Belton and Stewart, 2002; Bouyssou et al., 2006; Zopounidis and Pardalos, 2010; Velasquez and Hester, 2013; Korhonen and Wallenius, 2020) (See **Tables 3f,g** for further details).

Soft Elicitation

Soft elicitation, also known as problem structuring, is the process of asking problem owners, experts and stakeholders for the knowledge, perceptions, beliefs, uncertainties and values that a model needs to embody before being populated with numbers. Methods here help in problem formulation, structuring understanding: e.g., cognitive maps, soft OR, soft systems, prompts such as PESTLE and other qualitative tools. The output of soft elicitation can lead to the building of sophisticated quantitative models; and can also structure communications and deliberations with stakeholders. Exploratory data analysis and visual analytics are also relevant. Soft elicitation is, rather obviously, focused on the sense-making and modeling phase of decision making, but it also has enormous advantages in setting the frame for communication between all parties and thus applies in all three phases. Also there are many cases in which the clarity brought by framing the issues well has obviated the need for formal quantitative analysis. These techniques are useful in all of the Cynefin Spaces, though they come to the fore in the Complex and Chaotic Spaces In which sense really needs to be made (Rosenhead and Mingers, 2001; Checkland, 2013; Steed et al., 2013; Bendoly and Clark, 2016; Pyrko et al., 2019; French, 2021) (See **Table 3h** for further details).

Identifying Decision-Making Tools Appropriate to a Problem

No "one-size-fits-all" tool is available for managing every climate risk or, indeed, managing the same risk but in different contexts, urgencies or availabilities of resources. This section aims to provide a means by which a climate risk manager may appraise

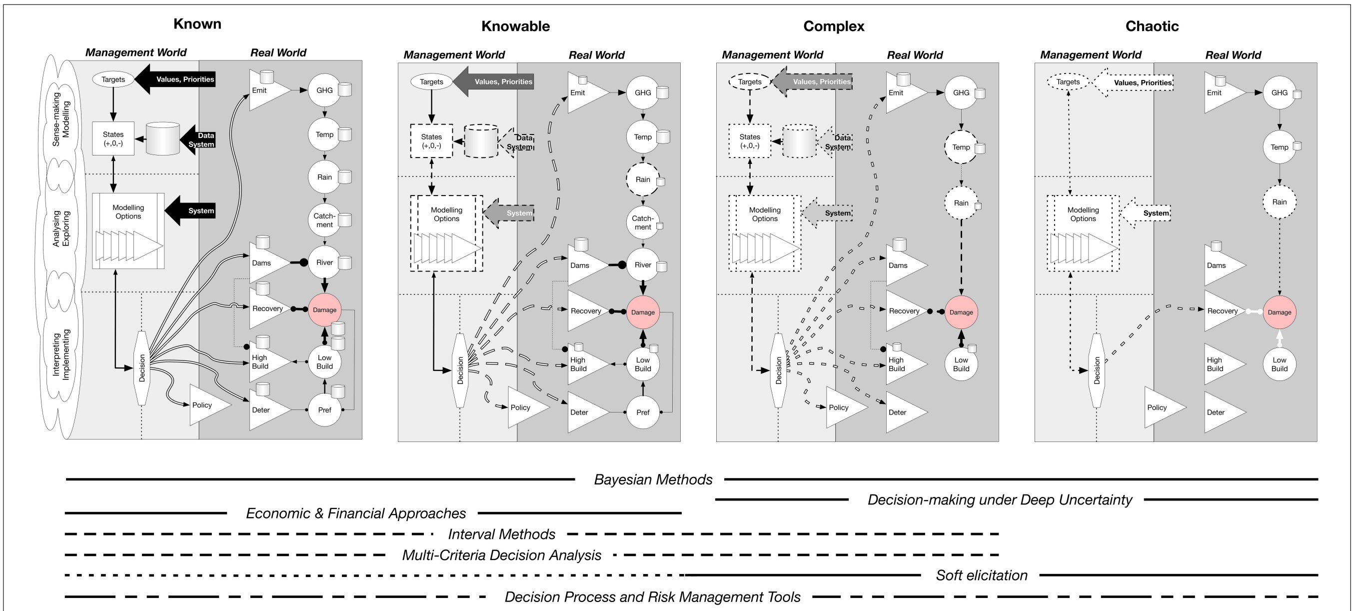

FIGURE 6 | Illustration of how a management system, including the extent of data and models, will differ between Cynefin contexts, following the example in **Box 2**. **Figure 3** is the Known context on the left. As uncertainty increases according to the Cynefin context (progressive panels toward the right), the ability to evaluate how the risk is changing in the future and to assess the implications of different actions will diminish. These changes are illustrated through change in the uncertainty around each subsystem and the linkages (see Legend in **Figure 3**) or even understanding what subsystems might be present. The interlinked and iterative processes between the three phases of a management system are shown in the cloud on the left. Text in the symbols are summaries of the text from **Figure 3**. The application of different approaches to decision analysis (see Section Approaches to Decision Analysis) applicable to the four Cynefin contexts are shown at bottom (solid line = broad application, dashed line = specific methods applicable, dotted line = applicable in some aspects such as in sense-making, double-dash-long-dash line = general useful).

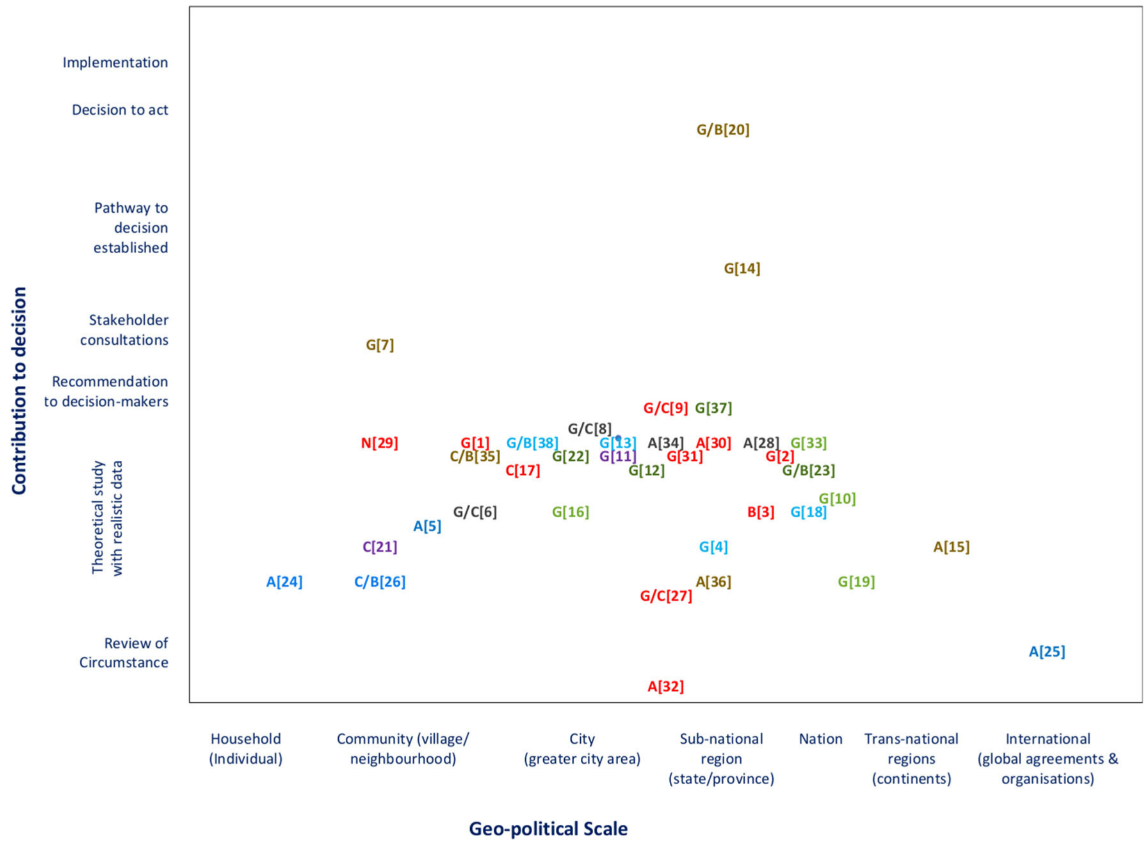

FIGURE 7 | A graphic relating case studies to (i) Geopolitical scale of a decision (ii) the commitment to the result of the case study, (iii) the decision-making bodies concerned and (iv) the decision analytic approach used. Symbols represent three components. Colour is the decision analytic approach: red, Bayesian; brown, Decision-Making under Deep Uncertainty; dark blue, Decision Process Management; purple, Economic and Financial Methods; light blue, Interval Methods; light green, full ranking MCDA; dark green, partial ranking MCDA; black, Soft Elicitation. Letters are decision-making bodies: C, Community; G, Government; B, Business/Industry; F, Finance; N, NGO; A, All categories. Numbers in square brackets are the citation: [1] Åström et al. (2014); [2] Alexeeff et al. (2016); [3] Baker and Solak (2011); [4] Batisha (2015); [5] Biehl et al. (2017); [6] Bosomworth et al. (2017); [7] Brown et al. (2019); [8] Butler et al. (2016); [9] Catenacci and Giupponi (2013); [10] de Bruin et al. (2009); [11] de Ruig et al. (2019); [12] El-Zein and Tonmoy (2015); [13] Gilbuena et al. (2013); [14] Groves et al. (2019); [15] Hall et al. (2012); [16] Haque (2016); [17] Jäger et al. (2018); [18] Kim and Chung (2013); [19] Konidari and Mavrakis (2007); [20] Lempert and Groves (2010); [21] Manocha and Babovic (2017); [22] Markl-Hummel and Geldermann (2014); [23] Michailidou et al. (2016); [24] Papathanasiou et al. (2016); [25] Parding et al. (2020); [26] Park et al. (2012); [27] Phan et al. (2019); [28] Prober et al. (2017); [29] Richards et al. (2016); [30] Richards et al. (2013); [31] Sperotto et al. (2017); [32] Sperotto et al. (2019); [33] Streimikiene and Balezentis (2013); [34] Symstad et al. (2017); [35] Taner et al. (2017); [36] Weaver et al. (2013); [37] Xenarios and Polatidis (2015); [38] Yang et al. (2018).

the value of different analytic techniques for their situation. We encourage a prospective user of these techniques to consider the nature of the control system they are dealing with, such as described in the box, the *Cynefin* context in which they find themselves, and the types of uncertainties most conspicuous in their case. **Table 3** can then be used to assess the appropriateness, or not, of different groups of techniques described above. The Table lists the various forms of decision analysis, indicating how they manage uncertainties, how they may be used in the different *Cynefin* contexts, how they fit into the different phases of decision-making and the resources needed in each use. In order to dig deeper into whether an approach may be suitable, citations are given to relevant literature to support our comments. In addition, we cite some relevant case studies in the application of the tools to climate-related risk management. We make no claims of exhaustiveness, and recognize that in identifying these characteristics we are making many subjective choices, but we hope that they offer a constructive guide into the literature that may help problem-owners and analysts find tools potentially valuable in their context.

While once-intractable, Bayesian Methods have made huge strides becoming computationally tractable and transparent to non-specialist users since the last century (Edwards et al., 2007). Moreover, developments in elicitation can be used to address behavioral and cognitive issues that can bias judgemental inputs (Dias et al., 2018; Turkman et al., 2019; Hanea et al., 2020). Many of the other methods evolved before these advances. Thus, Bayesian ideas should not be dismissed on those grounds; the main issue in using them is that they are explicitly subjective, emphasizing transparency, consensus, impartiality, and correspondence to observable reality instead of objectivity (Gelman and Hennig, 2017).

Different cultures recognize and value subjectivity and objectivity differently. Some demand that subjective judgements are recognized explicitly, while others only acknowledge objective issues explicitly.

Decisions are based on analyses of the knowledge and information at hand to the decision-maker. The context of the decision process described above influences what can be done in each phase of decision making. **Figure 6** illustrates how knowledge and uncertainty of the different subsystems in the example control system for managing the risk of consequences of flooding (**Figure 3**) influence the *Cynefin* space that the management problem may fall within, as well as indicating the analytic techniques that may be available.

Decision analyses used to support decision-making on climate-related risks shown as case studies in **Table 3** were assessed for the circumstances in which they were used. The first dimension of the assessment was the geo-political scale to which the decision was intended to apply—household (or individual), community (village or neighborhood), city (including the greater city jurisdiction), sub-national region (a state, province), nation, trans-national regions (within a continent), international (through global agreements, organizations and the like). This scale differs from the type of body making the decisions, which is reflective of whether the outcome is intended as top-down, autonomous, or bottom-up. Here, a top-down decision is one that applies from a body that is autonomous at higher geopolitical scale to lower scales, whereas a bottom up decision is one made by a body autonomous at lower scales intended to influencing high scale outcomes.

The second dimension relates to the contribution of the technique to decision outcomes. These contributions relate to phases in the decision process but, as described previously, may not be implemented in a set sequence. The types of contributions include:

Reviews of circumstance:	problem formulation, relationships between factors (related to the sense-making phase).
Theoretical studies with realistic data:	qualitative, statistical, dynamic modeling, scenario testing (sense-making as well as analyzing and exploring).
Recommendation to decision-maker:	appraisal of alternative actions (interpreting).
Stakeholder consultations:	occur at anytime, could relate to problem formulation, risk identification, consequences of actions (sense-making, analyzing and exploring, interpreting and implementing).
Pathway to decision-established:	finalization of actions, commitments without final approval or enacting regulations (interpreting).
Decision-implementation to act:	final outcome and course of action set in train (implementing).

The results of this assessment are shown in **Figure 7**. Evidence of the basis of actual decisions and whether decision-analytic techniques were used to support the making of those decisions is difficult to find in the peer-reviewed literature. Most of the case studies were related to theoretical studies with realistic data, reflecting that most literature on climate change is about scenarios and the consequences of those scenarios. Many fewer studies address the actual decision processes of managing climate-related risks. Moreover, the spectrum of different types of contribution to the decision process seem more focussed at subnational/national levels.

CONCLUDING REMARKS

Climate change brings many profound challenges and with them a need to manage a gamut of risks, ranging in scale from very local to global and severity from a relatively simple need to adapt to existential. Addressing these will involve many people, many decision-makers, stakeholders and experts. Some situations may have time and resources for acquiring data, opinions and to test options; others need urgent actions. In consequence, there are many decisions to be made and a great need for modeling and analysis to support these decisions.

In this paper, we have sought to guide policy makers, their advisors and the broader climate change community (scientists, NGOs, advocacy groups) into the literature on decision analysis and the range of tools available to support decision-making. We have sought to emphasize the complexity of decision-making, particularly in the context of time-constrained risk management. We have presented existing approaches and decision analytic tools in a way that we believe will help policy makers find methods that are appropriate to their circumstances. We hope that our paper stimulates their recognition of the complexities involved in the decision-making and at the same time offers constructive suggestions to help develop appropriate decision analyses.

AUTHOR CONTRIBUTIONS

SF and DV conceived of the paper. VK and SF undertook literature review and assessment. AC and DV provided coordination and climate-risk context. All authors contributed to the writing. All authors contributed to the article and approved the submitted version.

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