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Climate policy decision making in contexts of deep uncertainty - from optimisation to robustness

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ABSTRACT

Integrated assessment models are often used to evaluate the role of different technologies in meeting global climate goals. Such models have been criticised for failing to address the deep uncertainties and plurality of values that are fundamental to energy transitions. One consequence is that model scenarios overwhelmingly depend on large-scale carbon dioxide removal to hold warming to below 2 °C.

Here we propose an alternative approach using Scenario-Focused Decision Analysis (SFDA) as methods that embrace decision making under deep uncertainty. SFDA can accommodate a range of value sets and perspectives, and most importantly can integrate value-based decision-making in designing climate policy. We specifically consider Robust Decision Making (RDM) as an exemplar of SFDA for developing climate policy.

We outline an iterative five-stage framework for RDM using the role of carbon dioxide removal in long-term mitigation pathways as an example. The five steps comprise (i) participatory definition of goals, values, potential policy options and uncertainties; (ii) modelling the performance of policy portfolios across a wide range of future scenarios; (iii) visualisation and identification of portfolio vulnerabilities; (iv) analysis of trade-offs; and (v) development of policy strategies. SFDA, and specifically RDM, provide untapped opportunities for diverse actors to explore alternative mitigation pathways and evaluate the robustness of climate policy choices through "*deliberation with analysis*". In relation to carbon dioxide removal methods, RDM provides a framework for evaluating their potential for safely meeting climate goals in a societally acceptable manner.

1. Introduction

The Paris Agreement seeks to hold the increase in global average temperature 'to well below 2 °C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5 °C above pre-industrial levels' (UNFCCC, 2015). There is increasing awareness that with current delay in mitigation efforts, there will be a need for both mitigation and carbon removal efforts to limit warming to 1.5 °C (Jackson et al., 2017; Strefler et al., 2018). Furthermore, there are sectors of the economy such as aerospace, steel, cement and agriculture amongst others which will not be able to mitigate sufficiently rapidly to 2050 meaning that there will be residual emissions of an uncertain extent (Energy Transitions Commission, 2018). As a consequence, recent opinion pieces have explored the need to strongly pursue both deep cuts in greenhouse gas (GHG) emissions, and substantial net removal of GHGs from the atmosphere. Mitigation pathways produced through integrated assessment models (IAM) suggest these removals will be required in the coming decades and continuing well into the 22nd century (IPCC, 2014). However, the ability to remove CO_2 at scale would mean the development of a number of pre-commercial technologies and their rapid spread throughout almost every aspect of our modern markets at an historically unprecedented rate of technological diffusion (Peters et al., 2017). Carbon-dioxide removal (CDR) is expected to become amongst the largest global industries and to be extensive and pervasive in the fabric of our societies and economies (Committee on Climate Change, 2019).

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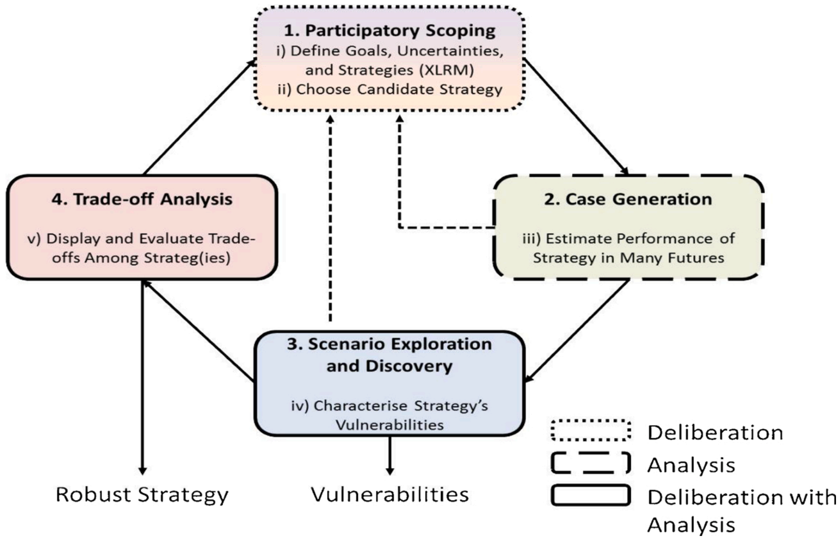

Fig. 1. The iterative, participatory steps (1 to 4) which characterise Robust Decision Making Analysis (Lempert et al., 2013). Parametric energy system models are mainly used in Step 2 and as such RDM involves a much more substantive extent of the decision making process than IAMs. An explanation of each component of the process is described in greater detail below.

There is a growing body of work which has called into question the application of IAM modelling when seeking to engage with the extent of uncertainty in policy (e.g. Castrejon-Campos et al., 2020; Floyd et al., 2020; Hoolohan et al., 2019 amongst others). The dominance of bioenergy with carbon capture and storage (BECCS) and Afforestation / Reforestation (A/R) in IAM mitigation scenarios emerges as a particularly problematic outcome of IAM scenarios. Workman et al. (2020) found that the widespread reliance on BECCS in these scenarios reflects a series of assumptions and structural features within IAMs as much as its value as a mitigation technology. However, we argue that a deeper problem is the degree to which these results and technologies have subsequently defined the framing of international emissions targets. The fundamental error lies in assuming that complicated models can define "optimal" pathways and strategies for which climate policy should strive, rather than providing exploratory tools to aid a broader policy development process.

In the case of BECCS, this is fuelling a polarised debate around the modelled reliance on large-scale carbon dioxide removal (CDR), which lacks engagement in the broader societal and policy implications of these technologies and hinders discussion of alternative innovation pathways. Workman et al. (2020) articulate an alternative approach that embraces multiple policy values, viewpoints and possible futures, in which modelling exists in an iterative exchange with policy development rather than being separate from it. Such an approach would support more relevant and robust near-term policymaking, ensure greater transparency and facilitate a more productive dialogue on the role of new technologies in climate policy.

In this paper, we develop an alternative framework using exploratory modelling tools - Scenario Focused Decision Analysis (SFDA) and specifically Robust Decision Making (RDM) - that seek to avoid the inadvertent and distortive effects arising from the dominance of IAMs in climate policy. In Section 2, we review the role of IAMs and other optimisation-based economic models as tools to explore climate change mitigation futures. We argue that optimisation tools, based on the construct of rational decision theory, are not well suited to many of the defining features of climate policy, in particular the diversity of values and actors, and the "deep uncertainty" around economic, environmental and sociotechnical futures. Section 3 explores how SFDA and RDM approaches could be applied to assessment of mitigation technologies and pathways, and Section 4 reviews how such methods could effectively address some of the persistent flaws in IAM interpretation.

It is important to address a number of framing issues before progressing. Firstly, we do not seek to negate the role of parametric complex systems modelling in climate policy design; indeed, we advocate that modelling has a critical function in policy design when the extent of uncertainty is suitable. Rather, we argue for the need to apply parametric decision support tools in a more appropriate way in climate policy design, as described using SFDA and RDM approaches as an exemplar to better manage uncertainty. Secondly, our main criticism regarding IAMs is not only that these models are not well equipped to handle the extent of uncertainty involved in climate policy design, but that they are used and interpreted in ways that neglect and compound these inadequacies. Robust Decision Making, effectively an ensemble approach incorporating a range of sub-processes (see Fig. 1), covers a greater extent of the decision making process both upstream and downstream than that which IAM covers to better illuminate the options and choices that can be made to attain robust policy design in the face of deep uncertainty. Finally, while the resources required to conduct RDM processes may be greater than those required to develop new IAM scenarios, the global policy implications of effectively addressing the threat of climate change justifies the additional resource allocation and effort. This is especially true given the burdens of climate change and the energy transition will be borne by everyone, justifying approaches that seek greater plurality, inclusivity and transparency in climate policy analysis (Nesta, 2019).

Therefore, the contribution of this article is: (i) to critique the construct of IAMs as tools to provide policy insight in contexts of deep uncertainty; (ii) to show that an overreliance on IAMs favours a narrow subset of mitigation pathways characterised by late-century carbon dioxide removal; and (iii) to suggest an alternative approach using RDM as an exemplar that can address these shortcomings. Using the role of CDR as a case study, we illustrate how RDM allows for uncertainties and supports a more open 'deliberation with analysis' via participatory and pluralistic processes. We argue that this not only makes policy more robust, but also more relevant to audiences by negating the ability to cherry pick solution sets or avoid problematic outcomes and their implications.

2. Uncertainty in global energy system modelling

2.1. The role of modelling in framing climate policy

Policy formulation can be described as an analytical community undertaking evidence gathering and analysis, while a policymaking

Table 1
Uncertainties in climate policy based on optimisation modelling (a) within the modelling process and (b) between modelling and policy design.

a. Integrated Assessment Modelling Process

- **Stochastic uncertainties:** physical randomness of the climate, social and technical systems which models are simulating.
- **Epistemological uncertainties:** uncertainty in defining the current status of technologies, social and economic variables, climatic processes etc.
- **Ontological uncertainty**: entities, interactions and processes occurring that are not yet contained in analysts' conceptual models of the world (Lane and Maxfield, 2005).
- **Computational uncertainties:** inaccurate calculations as a function of rounding errors e.g. Lorenz, 1963 and the butterfly effect.
- **Scope uncertainties:** processes generating important changes in the real world that are not captured by or within the scope of a given model, e.g. political dynamics or innovation.
- **Judgement uncertainties:** the setting of parameters and convergence criteria in codes that parameterise the models. The complexity of IAMs in particular make these substantive. They are rarely disclosed in an explicit manner to external audiences (Pindyck, 2013).
- **Modelling errors:** however good the model is, it will not fit the real world perfectly.

b. Pervasive across climate policy design including interaction between analytical and policymaker communities

- **Endpoint uncertainties:** when the required endpoint is ill-defined - this is manifest in the coupling of carbon budgets and temperature targets which are far from rigid or in the exact emissions that are sequestered and/or emitted from bodies of land at different latitudes.
- **Semantic uncertainties or ambiguities:** ill-defined meaning of terminology and wording which will be prevalent across the multiplicity of disciplines, ontologies and domains that integrated models seek to describe, and how they are communicated to policymakers (Lane and Maxfield, 2005).
- **Implicit value judgements and/or preferences:** no matter how well-intentioned modellers or policymakers are, value trade-offs will have to be made when designing policy. In optimisation modelling, the terms of such trade-offs are usually implicit in the choice of goals, constraints and metrics, and may not reflect those of the policymaking community or wider publics (Stanton et al., 2009; Keeney, 2002; Vezer et al., 2018; Elliott, 2017; Helgeson, 2019).
- **Implementation uncertainty:** uncertainty in the effectiveness of the policies in the idealised simulation trajectories output by climate models when implemented in the real-world.
- **Ethical uncertainties**: what is 'right' and for whom? Who defines policy goals and acceptable trade-offs? Such issues are being unpicked in the just transitions and climate equity literature (Kartha et al., 2018; Green and Gambhir, 2019).

community debates, negotiates or further develops policy for enactment based on potential outcomes and acceptability. Popper (2019) distinguishes these two cultures as a numerate, reductionist analytical community, rooted in deductive logic, while the culture of policy is more narrative based and framed in the logic of abductive reasoning. The culture of policy considers questions of the future: *"How will we be affected if present trends continue? What could go wrong if we follow this course or that? If the circumstances we most fear come to pass, how will we cope?*".

The concept of "policy paradigms" (Carson et al., 2009) highlights that rather than a clear cut distinction between analytical and decision making functions in policy design, divergent interests, agendas and values shape policy-making. The role of co-production and boundary work around science and policy in conferring legitimacy on analytical policy inputs is well documented (e.g. Beck and Mahony, 2018; McLaren and Markusson, 2020). However, beyond the politics of climate policy, the psychology as to how decisions regarding policy are actually formulated, the role of detailed analysis and expertise such as that involved in parametric modelling in the process of policy development, and its role in final policy output and decision-making has had limited research and is therefore poorly understood (Conway and Gore, 2019). What is known is that heuristics and biases are prevalent, particularly around issues involving substantial uncertainty and that the dialectic process between the analytical and policy making communities is marked by very different cultures, processes and lexica (Tverskey and Kahnaman, 1974; Kahnaman and Tverskey, 1984; Klein et al., 2007; Kahneman and Klein, 2009; Klein, 2013).

With the increase in computer power and available data allowing the development of more complex tools, the role of modelling in climate and energy policy has been increasing (Pollitt, 2018). Furthermore, the relative weight placed on model results has increased over the last 10 years (European Commission, 2015, p32). Therefore, understanding how IAMs gain legitimacy in climate policy, and their appropriateness for contexts of deep uncertainty, is of paramount importance. Ultimately, closer engagement between analytical and policy communities would allow for a more critical interrogation of mitigation scenario development (Dooley et al., 2018; Sutherland and Burgman, 2013; and Tyler, 2013). Especially avoiding the `*fallacy of misplaced concreteness'* which is associated with parametric outputs (Whitehead, 1929).

IAMs have historically been developed within the analytical community to provide insight into the global implications of different societal, policy or technological scenarios (Haikola et al., 2018). They assist in identifying technical and policy solutions by representing the world's energy, agricultural and land emissions, and implicitly their interaction with societal systems, over a time period spanning from the present to the end of the 21 st century (Anderson and Jewell, 2019). While IAMs are not typically direct inputs for designing national policies, they have had an important role in framing what are seen as plausible and cost-effective pathways and technologies for meeting internationally agreed climate targets (IPCC, 2014; Gambhir et al., 2019).

While many critiques have been made of integrated assessment modelling (Gambhir et al., 2019), here we focus on the characterisation of the uncertainty that is being encountered. We argue that a better understanding of the uncertainty, complexity and irreducibility of the future option space reveals the inadequacy of even the most elaborate of optimisation-based tools to reconcile the range of possible futures over the timescales considered by IAMs. Instead, recognising the character of international climate policy discourse as one of deep uncertainty would justify application of a broader suite of tools.

2.2. Thinking under uncertainty

Lempert et al. (2003a), 2003b define "deep uncertainty" as a circumstance:

> *where analysts do not know, or the parties to a decision cannot agree on, (1) the appropriate conceptual models that describe the relationships* among *the key driving forces that will shape the long-term future, (2) the probability distributions used to represent uncertainty about key variables and parameters in the mathematical representations of these conceptual models, and/or (3) how to value the desirability of alternative outcomes. In particular, the long-term future may be dominated by factors that are very different from the current drivers and hard to imagine based on today's experiences.*

By this definition, the future development of novel technologies within the broader evolution of the global socio-political and techno-economic systems to address international climate goals represents a clear case of deep uncertainty:

1) Whilst there is some consensus on conceptual models, including use of global energy models and earth system models, there remains considerable uncertainty about the key driving forces over these timescales; furthermore, scenarios that attempt to describe the latter are often limited by their normative design (Pindyck, 2013; Rosen and Guenther, 2015).
2) There is significant uncertainty about key variables such as availability, cost and effectiveness of technologies, social preferences and political contexts. For example, many CDR technologies represent

novel innovations for which there is no large-scale track record (Anderson and Peters, 2016).
3) There is little agreement on how to value and trade off alternative possible outcomes on metrics such as equity, economic benefits, preservation of biodiversity etc. Fundamentally, all such questions are subject to opposing ethical, philosophical and political views (Beck and Mahony, 2018; Dooley et al., 2018).

Even defining the suite of technologies that policy makers will have at their disposal in 50–80 years' time is subject to substantive - especially ontological – uncertainty (US National Academy of Sciences, 1937 after Rees, 2003). The costs and societal responses associated with these technologies are yet more uncertain. For example, 80 years ago nuclear power and smartphones were not yet imagined, they are now integral to global energy systems and societal fabric. Yet the technology suite applied to energy systems in IAMs to 2100 seems very similar to that of today (Gambhir et al., 2019).

As an illustration of the depth of uncertainty in modelling complex sociotechnical systems, Table 1 presents a list of the uncertainties associated with developing climate policy on the basis of IAM outcomes, including those inherent in the modelling process and those arising from the interpretation of model outcomes in policy design (French et al., 2019).

Addressing these uncertainties within the IAM framework is not trivial. There have been recent attempts to explicitly assess the extent of uncertainty in IAM outputs. For example, Marangoni et al. (2017) conducted a thorough sensitivity analysis of the key drivers of uncertainty in long-term CO_2 emissions across the Shared Socioeconomic Pathways using several major IAMs. However, such descriptive assessments conducted within IAM frameworks do not address the non-quantitative uncertainties such as those defined in Table 1 (Pindyck, 2017; Pye et al., 2018), and are not readily reconciled with the use of models as prescriptive tools.

While it is good practice to be completely transparent about uncertainties (French et al., 2019), this transparency is both a significant communications challenge, and is lacking in practice between the IAM and policy communities (Haikola et al., 2018). Indeed, in the context of international climate policy, the models produce point estimates and the modellers do only limited sensitivity testing. If uncertainty analysis is done at all, it is often undertaken retrospectively by policy makers (Anderson and Jewell, 2019; Dooley et al., 2018) but many policy analyses lack a serious assessment of uncertainty (e.g. European Commission, 2020). Rather than sidestep uncertainty or deal with relatively minor elements of uncertainty we suggest that policy makers should adopt decision making tools that embrace the deep uncertainty of climate policy.

2.3. From consolidative optimisation to simulation to exploratory modelling

Besides treatment of uncertainty, the use of IAMs to select cost-optimal solutions also undermines flexible and transparent decision making. IAMs are typically grounded in an equilibrium modelling philosophy (Bolwig et al., 2019; Mercure, 2019). The market (or an imagined social planner) is assumed to maximise utility by allocating resources optimally at each point in time in order to meet given goals at a minimum cost.

Equilibrium models commonly also assume perfect (or at least probabilistic) knowledge of the future in order to find the optimal outcome, and this model-selected outcome is considered a "normative or aspirational" scenario to be pursued by policymakers. Such consolidative models gather all relevant knowledge into a single package which, once validated can be used as a surrogate for the real world and tend to be used for predictive exercises (Bolwig et al., 2019). However, in optimising for pre-defined goals and parameters, they can be sensitive to false assumptions, and tend to obscure both the value judgements implicit in their goals and alternative pathways for achieving them.

Other authors have thus sought to soften the cost-optimisation criterion to generate a wider range of possible solutions sets. Price and Keppo (2017), for example, used the TIAM-UCL model to generate a set of maximally different energy system transition pathways that were "near cost optimal". While usefully expanding the range of options to be considered, this approach remains grounded in an optimisation framework, neglecting both widespread uncertainties in cost estimates and the importance of other variables in determining feasible or desirable policy choices.

A contrasting approach is non-equilibrium modelling (Mercure, 2019), which views the economy as consisting of multiple actors making decisions with imperfect knowledge of the future. This philosophy views the economy as a complex dynamical system, and models in this school aim to be "simulations" of real-world behaviour in response to changing conditions. Such a simulation-based approach seeks insights as to what might happen to a system following a change in an important driver such as introduction of a new low carbon technology or policy. Responses are based on predictions of real-world behaviour using historical or econometric datasets (Pollitt, 2018). Crucially, models are not used to internally select an optimal scenario, but to map out possible trajectories arising from different policy choices. However, even sophisticated simulations depend on making best-guess predictions about the behaviour of the economy, whether through economic theory or econometric data, and thus also face challenges in addressing deep uncertainty on timescales of energy system change.

An extension of the simulation approach is exploratory modelling which maps assumptions onto consequences without privileging any one set of assumptions, and thus supports iterative problem-solving (e.g. Kwakkel and Pruyt, 2013). The use of exploratory modelling mitigates many of the challenges of designing policy based on optimisation modelling, and situates modelling within the policymaking process (aiding policy impact assessment) rather than upstream of it (defining normative policy goals).

There has been increasing recognition of the limits of purely techno-economic analysis to provide insight into decarbonisation transitions (Floyd et al., 2020). Several recent studies have sought to develop approaches that combine quantitative, model-centric methods with participatory, qualitative and scenario-based processes (Moallemi and Malekpour, 2018). Such combined approaches have started to explicitly engage with the extent of uncertainty in energy transitions (Castrejon-Campos et al., 2020). It has been argued that the increasing use of participatory processes can help stakeholders reach a shared problem definition, reconcile multiple competing goals and explore a wider range of solution sets than in model-led approaches (Hoolohan et al., 2019) to envision and adapt to surprises (Sharmina et al., 2019); and to increase flexibility and transparency in strategic planning (Pereverza et al., 2019).

These recent contributions provide critical mass to the appropriate application of modelling tools to address uncertainty and the importance of participatory processes to elicit robust outcomes (van der Voorn et al., 2015). We aim to build on these efforts by detailing the application of RDM methods to explore robust pathways to meeting international climate targets.

3. From Optimisation to Robustness: how Robust Decision Making could open up the assessment of climate change mitigation pathways?

3.1. Scenario Focused Decision Analysis and Robust Decision Making

We now introduce Robust Decision Making (RDM) as an exemplar of a group of tools we define as "Scenarios-Focused Decision Analysis", and outline how they can support resolution of the issues raised regarding the application of IAMs to international climate policy design, particularly with respect to the role of CDR technologies.

Table 2
From optimisation to exploration. Comparing the consolidative approaches of Optimisation (Paradigm 1a) and Simulation (Paradigm 1b) to the exploratory approach of Robust Decision Making (Paradigm 2). Adapted from Stern et al., 2013 and Pollitt, 2018.

Optimisation (Paradigm 1a) - seeking optimal outcomes under fixed assumptions, where markets or actors have perfect knowledge of future conditions and minimise costs through optimally allocating resources.
Goal: Figure out your best-guess future and design the best policy you can for that future. ***Conceptual framework:*** Optimisation and Maximize expected utility ***Question:*** 'What is most likely to happen?' ***Observations:*** • Can be efficient but limited applicability to more simple cases / systems. • Often ignores or simplifies wider interpretations of value and non-quantified benefits. • This tends to result in the best-characterised technologies being overly favoured in modelling processes e.g. BECCS. • Favours approaches that (cost) efficiently meet goals within model assumptions over examining plausibility of approaches or assumptions.
Prediction-based simulation (Paradigm 1b) - seeking real world input via econometric data. Simulation studies avoid optimising but instead create best guess predictions based on real world datasets for the outcomes of various proposed policy packages to assess the impact of an intervention to the system.
Goal: Figure out what will happen in response to a change in the system such as a new policy. ***Conceptual framework:*** Represent real world behaviour using analogous data; not optimisation. ***Question***: How will the system respond to a new intervention based on analogues from real-world data. ***Observations:*** • Social systems can be very hard to embed into models as they operate in different ways to the physical systems. There are often gaps in the knowledge base and irrationality of sub-components of social systems can be problematical to model. • Should avoid monetising impacts into a Cost Benefit Analysis as that effectively indirectly cost optimises. • The lack of real-world roll-out of novel technologies such as CDR, and the limited social science research activity in the CDR space, means there are few datasets to provide constraints on technology adoption and impacts. • The introduction of econometric social system dimensions to simulations would likely result in substantially reduced maximum CDR presence in the models and much slower diffusion rates as that for optimisation but would still struggle to reconcile the extent of uncertainty.
Robust Decision Making (Paradigm 2)– whereby the goal is to explore and manage, rather than characterize Deep Uncertainty
Goal: Identify greatest vulnerabilities across full range of futures and identify the suite of policies that perform reasonably well across this range. ***Conceptual framework:*** Minimize regret and assess assumptions. ***Question:*** 'How does the system work and when might the policies applied fail?' ***Observations:*** • An RDM framework offers greater insight into policy vulnerability and facilitates the selection of robust portfolios of options across multiple possible scenarios. • Concerns regarding reliability and technology uncertainty can be explicitly incorporated in an RDM framework, allowing testing of possibilities such as failure in scale up. • Multiple audiences including policy/decision makers can be brought into the process to ensure value sets are integrated into the process.

Scenarios-Focused Decision Analysis (SFDA) describes a family of methods that aim to explicitly characterise (deep) uncertainties within scenarios, and then undertake decision analysis within and across these scenarios (French et al., 2019). The role of scenarios and their employment in decision making under many forms of uncertainty and complexity is a growing field. Guivarch et al. (2017) explore how new decision support techniques address the uncertainty/complexity space and reconcile multiple objectives and scales. Trutnevyte et al. (2016) discuss focal points for reinvigorating the scenario technique to help scenario developers and users expand uncertainty consideration. Derbyshire (2020) highlights the narrowness of common practice in both scenario planning and policymaking, and how SFDA can help address the inability of these to consider ontological uncertainty. The need to understand the comparability of the different techniques and how they can be brought together to build on strengths of each other demonstrates the nascent and emergent nature of this field.

Here we use RDM as an exemplar of an SFDA approach due to its broad employment over 15 years (Lempert et al., 2003a, 2003b). The basis of RDM approaches are articulated by Dessai and Darch (2014) in that `*Whereas traditional decision-making processes seek optimality, RDM approaches accept uncertainty and focus on robust strategies….'* i.e. strategies that are better able to accommodate a wider range of uncertainty. The key tenets of the RDM approach in contrast to optimisation-centric methods are:

1 RDM embraces uncertainties in all forms and works with these to identify solutions that are robust;
2 RDM is a participatory and iterative process, from the design of performance metrics through to the trading-off of solutions between decision makers and analytical community through "deliberation with analysis";
3 RDM is compatible with adaptive pathway approaches which (a) identify low regret solutions for implementation in the short-term, and (b) identifies triggers for the deployment of alternative strategies, taking into account lead times for solution development; and
4 RDM reflects how effective decision making is practiced in real situations in conditions of deep uncertainty (Klein et al., 2007).

RDM analysis can allow for climate policy and technology options, including CDR, to be treated in a more nuanced manner, taking account of the co-benefits and drawbacks, and drawing on the practice and policy implementation, resulting in more implementable options. RDM is also well suited to a more bottom-up approach, potentially supporting the framework of the Paris Agreement which allows nations to submit their Nationally Determined Contributions (NDCs) to the UNFCCC (Waisman et al., 2018). Table 2 summarises the shift in the philosophy from a consolidative IAM-based optimisation approach, the application of simulation based approaches, to an exploratory RDM approach and the way that models can be used to inform international climate policy as to the role and extent of CDR in possible climate futures.

3.2. A potential RDM process for evaluating global mitigation pathways

Here we articulate how RDM could be applied to evaluating a specific suite of climate policy options related to atmospheric carbon dioxide removal. RDM could be applied at the global scale, providing an alternative to the current context of IAM use, and could also be applied to national policy development based on country-specific analyses. The steps related to the RDM process are outlined in Fig. 1, and further explained below. The framework set out in Fig. 1 is malleable depending on the circumstances. In this paper, we suggest a potential framework for conducting a robust decision-making analysis of global mitigation pathways, using the potential role of CDR as an example.

3.2.1. Step 1: participatory scoping

The process, as illustrated in Fig. 1, first begins by defining the goals, metrics, uncertainties, and choices or options that are available. Typically, this step is participatory. This presents a challenge for a global policy problem, but could be constrained by a group of representative stakeholders, or by reference to commonly used appraisal objectives. Ethical uncertainties (Table 1) are an important consideration at this point and goal identification should be broadly scoped. Much of the effort in a participatory approach - but also the value - arises from overcoming semantic uncertainties and ambiguities and developing a meaningful understanding of stakeholder ontologies and objectives.

However, "problems of deep uncertainty should be addressed superficially at first" (Popper, 2019) meaning that formal models are not necessarily required, especially at first. The modelling is developed and modified through several iterations, facilitated by the participators' deliberations. As there should be many iterations of the analysis, this provides numerous opportunities to engage with wider diversity of stakeholders and their deliberations. Thus, the key participants in the early iterations are the policy makers.

This step can use the Exogenous Variables-Policy Levers-Relationships-Measures ('XLRM') framework to identify exogenous uncertainties, levers or measures, relationships between the uncertainties and measures (typically captured in a model, see Step 2), and metrics to define performance against goals (HMG, 2009).

Goals can include temperature target(s), a need for cost efficiency (e.g. select options according to a marginal abatement curve), minimisation of environmental impact, food security, considerations of equity, etc. High-level goals can be subjective, but if they are to be part of the trade-off process (described below) they require a quantified or scaling metric e.g. meet a 2 °C temperature limit, minimise costs. Endpoint uncertainties (Table 1) can be represented by alternative goals, or by setting ranges. Defining metrics can be a complex process that requires some testing and iteration.

Uncertainties should cover factors that may affect the system and are likely to be broad. These include stochastic, epistemic and endpoint uncertainties (Table 1). These uncertainties can be drawn from Political-Economic-Social-Technical-Legal-Environmental (PESTLE)-type guides to allow the more explicit unpacking of the broader considerations that are needed to realise different scenarios (Government Office for Science, 2017). Uncertainties can be represented using exploratory scenarios, either created specifically or by using or adapting existing scenario sets.[1] Key factors are likely to include economic growth, social attitudes, costs, effectiveness and scale-up of technologies, and the political environment.

Strategies should focus on identifying options or measures for realising climate goals. As discussed above these can be taken from existing normative scenarios and associated studies, and in doing so a wider variety of options could be sought. Initially options should be considered at a discrete level so as not to conflate characteristics, e.g. between different combinations of value chain options (Platt et al., 2018). It may be helpful to categorise measures into different types.

In the case of CDR, this stage may include grouping technologies into categories and defining relevant uncertainties, risks and enabling conditions. For example, "no-regrets" options with co-benefits (e.g. restoration of degraded ecosystems and soil carbon) may raise certain issues, while options dependent on CCS technology may be subject to other vulnerabilities and prerequisites (Caldecott et al., 2015). Options need to be described in sufficient detail to be characterised and included in the modelling. This will require estimates of lead-in time, capital and operating costs, scale of deployment including uncertainties associated with these variables, etc., again allowing greater fidelity on the part of the modellers and policy community to better comprehend what is required to introduce and scale up different technologies.

3.2.2. Step 2: case generation

The next step uses a wide range of potential future scenarios to assess the performance of options. Typically, options are integrated into portfolios, each of which collectively meets a minimum performance level such as reaching defined temperature goals. Aggregation can be undertaken 'manually' or through modelling, for example using multi-criteria search.[2] This would not require abandonment of normative, goal-oriented scenarios. Rather, the portfolio of measures that these scenarios incorporate could be used as candidate portfolios. Alternative portfolios can also be developed, or an RDM process can be designed to automatically search for candidate portfolios by combining individual measures. In addition, the RDM process requires a large set of exogenous scenarios that are used to test the candidate portfolios (see Step 3).

Robust Decision Making generally uses models to assess the performance of candidate portfolios. The models must describe the relationship between measures and scenarios, such that the former can be tested by the latter. Such models could themselves be IAMs or an emulation of these. To ensure robustness a very large number of scenarios is typically used, often in combination with a large variety of portfolios. Therefore, the model chosen should be adaptable and fast to run, though the associated processes around the agreement of the parameterisation of the models can be substantive (Gambhir et al., 2019) and model-related uncertainties are better represented using exploratory modelling approaches (Castrejon-Campos et al., 2020).

To evaluate CDR, a model should be chosen that effectively represents key technology groups and associated issues, e.g. carbon storage in vegetation and soils.

3.2.3. Step 3: scenario discovery

The analysis of this data from all the scenarios (generated in step 2) is then processed and visualised, which helps decision-makers identify policies' vulnerabilities, new opportunities, and new scenarios and uncertainties for exploration. This step can be assisted by algorithms such as cluster analysis, which identifies the circumstances that lead to good performance or failure. It may be that there are easily identifiable scenarios under which some or all portfolios fail; this helps to understand existential vulnerabilities to objectives that no combination of measures will be able to address. This again allows better insights and understanding as to what the scenarios involve in order to realise solution sets - getting away from the perception that the models are able to characterise the future.

In simple terms, candidate portfolios will be rejected if they do not meet all minimum criteria; visualisation techniques can facilitate the selection/rejection of portfolios including via a trade-off analysis or exercises (Step 4). The performance of policy portfolios can be assessed and incorporated in different ways depending on the nature of the RDM process used. For example, portfolios could be rated according to their cost, deliverability and environmental impact, with these metrics then incorporated into the trade-off process - see Step 4, below. Alternatively, measures within portfolios could be introduced at a later point in model time (for example if using multiple 'time-slices').

Combined with a pathways approach, this could then illuminate how to achieve goals if CDR options failed, or were less effective or extensive than anticipated (Haasnoot et al., 2013). This would then force policy makers to better understand how the different scenarios have been developed and what they would involve in terms of policy interventions

[1] For example, see scenarios from IPCC, Millennium Ecosystem Assessment, Shell, UNEP (GEO-4).

[2] For example, see Matrosov, J., Huskova, I., Kasprzyk, J.c., Harou, J., Lambert, C. and Reed, P. 2015. Many-objective optimization and visual analytics reveal key trade-offs for London's water supply. Journal of Hydrology 531 (2015) 1040–1053.

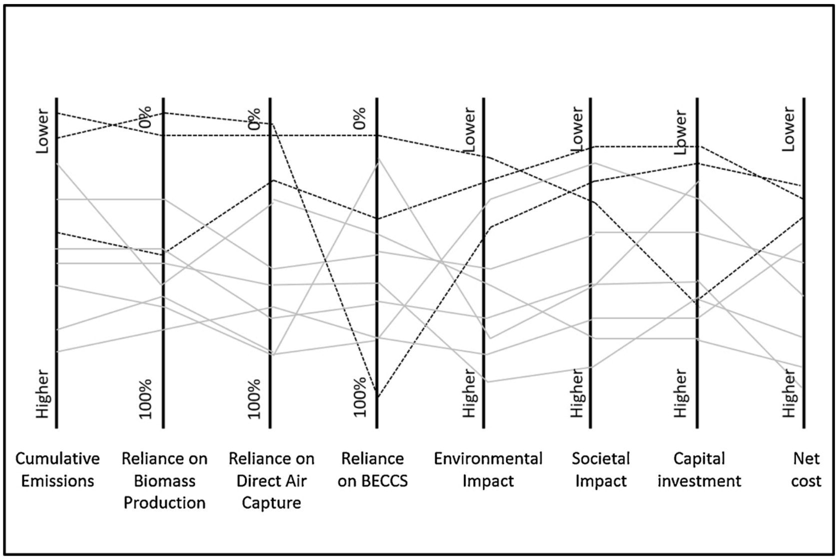

Fig. 2. Illustration of Trade-off Analysis in RDM strategy development accounting for, in this particular example, parameters related to CDR deployment.

to realise. Implementation uncertainties (Table 1) can also be explored by altering performance according to the scenarios (or states of the world) or in alternative portfolios.

3.2.4. Step 4: trade-off analysis

Optimal performance when considering many metrics generally involves some compromise. For example, there tends to be an inverse relationship between cost efficiency and reliability. This step is concerned with trading off metrics and 'satisficing', i.e. deciding what is a reasonable balance. Wider considerations regarding shortlisted option portfolios may also be considered at this point.

Ideally this step involves real trade-offs between stakeholders, including information on values-based metrics such as human rights, food security or biodiversity protection which can be problematical to trade off. The need to integrate values in decision making is fundamental when designing climate policy; it is integral to ensuring plurality, engagement with broader constituents, and forces transparency to develop trust amongst audiences. However, the role of transparency and relevance in decision support is under-researched (Bessette et al., 2017; Mayer et al., 2017; Casey Helgeson, 2019) and values can be mishandled in analysis (Keeney, 2002; Vezer et al., 2018; Elliott, 2017; Helgeson, 2019).

The role of the integration of values, transparency and trust is integral to the RDM process and would address many of the issues regarding the polarisation around the CDR discourse raised in Colvin et al., 2019. Trade-off analysis could be invaluable in answering key policy questions such as:

- What proportion of CDR portfolios meet fixed temperature targets?
- Which CDR technologies are commonly selected and why?
- What the key trade-offs between CDR options and other values?

There are several techniques for visualising and implementing the trade-off process including multi-dimensional and parallel axis plots. Software such as Polyvis[3] can be used to highlight which portfolios are included or excluded based on the desired metric performance and trade-offs between metrics (see Fig. 2, below). In this type of figure, portfolios of options are represented by left-right lines, with their performance measured against goals depicted by vertical axes. Trade-offs between goals are required where portfolio performance lines cross.

[3] Polyvis.org.

3.2.5. Feeding RDM into the climate policy process

A final step is to use the preferred portfolio (or portfolios where there are synergies) to develop a suite of climate policies (Friedman, 2013). The steps described above are typically undertaken for a fixed point in time or 'time-slice' (average period of time) to produce a robust portfolio. Developing a set of climate policies which includes ordering of options can be achieved by evaluating the options using simpler optimisation techniques (e.g. based on cost, size, feasibility) or/and using multiple future time horizons as a guide. A more robust approach would be to use methods that formally evaluate alternatives and the potential for regret (such as failing to meet a target, or the construction of assets that later become stranded). Such methods include Real Options Analysis (HMT, 2013), Least Worst Regrets Analysis (Zachary, 2016; Ministry of Housing, Communities and Local Government, 2009; Loomes and Sugden, 1982; Bell, 1982 and Fishburn, 1982) and adaptive planning techniques (Haasnoot et al., 2013 and Maier et al., 2016).

Applied to CDR, such an approach could highlight alternative pathways that better manage trade-offs and uncertainties associated with large-scale deployment of developing technologies.

4. Implications and benefits of the use of RDM in climate policy development

4.1. An RDM approach addresses key issues of global policy discourse dominated by IAMs

Table 3 highlights how when, applied transparently, within an inclusive, participatory decision-making framework, parametric decision support processes can lead to substantively different policy outcomes. By seeking vulnerabilities in proposed policy measures, RDM can illuminate alternative pathways to meet key challenges identified through modelling. For example, in the case of BECCS, considering the failure to develop carbon capture and storage infrastructure would force policy-makers to explore alternative ways of addressing the roles played by BECCS in IAMs, including the development and scale-up of dispatchable clean power, addressing of residual emissions in different industries, integration with low-carbon sustainable biofuels, and achieving net negative emissions.

RDM is explicitly designed to manage uncertainties by seeking solutions that are robust to unknowns. The role of RDM in addressing different types of uncertainties has been described at each step in the process (see Section 3) and is summarised in Table 4. The Participatory Scoping step (the first step) is the most important given its influence on

Table 3
How RDM could address the distortive effects introduced by IAMs into long-term climate policy (Workman et al., 2020).

1.	**IAM development is a closed community with limited engagement of societal audiences or policymakers during the modelling process.**	RDM is a participatory process, involving all these stakeholders in the design and evaluation.
2.	**IAMs optimise for a fixed set of assumptions.**	RDM embraces uncertainty and uses exploratory scenarios to test a wide range of candidate strategies; the latter can include normative goals but is flexible and can evaluate any combination of solutions.
3.	**IAMs are perceived as evidence of attainability of climate targets.**	RDM exposes the fragility of portfolios that are not robust to future uncertainties. Furthermore, it can evaluate the performance of solutions that are at different level of technology readiness.
4.	**IAMs require pre-defined assumptions and technology characteristics and suppress certain categories of uncertainties.**	RDM exposes fragility of portfolios to a range of uncertainties identify low-regret measures and longer-term strategies that are robust across a range of outcomes.
5.	**Large-scale reliance on certain technologies in IAM simulations for attaining climate targets lead to a polarising discourse.**	RDM can explicitly trade-off available technologies against cumulative emissions or/and temperature targets.
6.	**IAMs introduce immature technologies needing to scale at rates unprecedented for such an infrastructure-intensive value chain.**	Technology Readiness Level can be built into solution evaluation for RDM; adaptive pathway approaches can incorporate lead times.
7.	**IAMs lead to a lack of appreciation of the scale of the upstream value chain which needs to be developed to realise negative emissions on the scale simulated to meet climate targets, nor the trade-offs which need to be considered.**	Upstream metrics could be incorporated into the trade-off process in RDM e.g. how land availability is decided and potential trade-offs (and synergies) on food security and biodiversity protection.
8.	**Limited portfolio of solutions is selected in IAMs.**	RDM will test a wide range of portfolios that include significantly lower and higher levels of different technology options.
9.	**The need to develop political will, values or social acceptance around new technologies and their associated value chains are omitted in IAMs.**	Values and social acceptance can be built into the trade-off process for RDM.
10.	**Deferment of near-term climate action, technology innovation and value chain development in IAMs.**	Adaptive pathway approaches can incorporate lead times and be reflected in the trade-off process in RDM.

setting the framework for the whole process. The modelling is developed and modified through the iterations facilitated by the participators deliberations. The transparency and participatory nature of the process supports participants and observers in challenging assumptions and reasoning. This improves robustness, the primary aim of the RDM process, as well as driving better understanding of the conceptual models used to represent the system (e.g. partially addressing judgement uncertainties). Some uncertainties are not addressed by RDM specifically (e.g. computational uncertainties, modelling errors and model-related judgement uncertainties); approaches such as exploratory modelling (Castrejon-Campos et al., 2020; Moallemi and Malekpour, 2018; and Kwakkel, 2017) can be used to address these.

4.2. Policy interpretation and development in RDM approaches: a new relationship between analysis and decision-making

As articulated by Popper (2019), tools for decision making under uncertainty, and specifically RDM approaches, would assist policymakers to articulate more robust climate policy portfolios through the following key features as articulated in Table 5, below.

Table 4
How RDM could address uncertainties in climate policy based on optimisation modelling (a) within the modelling process and (b) between modelling and policy design.

a. Integrated Assessment Modelling Process	
Stochastic uncertainties	The ability to represent these may be conditional upon the model used, although some can be represented as scenarios e.g. climate processes.
Epistemological uncertainties	These can be represented as alternative scenarios (e.g. states of the world) or in different options.
Ontological uncertainties	Additional knowledge should be used to improve models, but some uncertainties can be represented
Computational uncertainties	These relate to the system models used rather than the RDM process per se.
Scope uncertainties	These apply to models but the participatory scoping phase of the RDM process will seek a broad scope.
Judgement uncertainties	These relate to the system models used. However, the participatory nature of the process should facilitate a meaningful understanding of key assumptions in the modelling process.
Modelling errors	These relate to the system models. Assurance activities including independent checks should provide confidence to stakeholders.
b. Pervasive across climate policy design including interaction between analytical and policymaker communities	
Endpoint uncertainties	These can be represented as alternative goals or expressed as ranges.
Semantic uncertainties or ambiguities	The participatory scoping phase should seek to overcome this and should be part of long-term engagement between stakeholders in understanding others' ontologies and objectives.
Implicit value judgements and/or preferences	Goal setting, metric definition and the trade-off process are designed to make the implicit explicit.
Implementation uncertainty	These can be represented in conjunction with exogenous uncertainties (e.g. the effectiveness of portfolios can depend on states of the world) or in alternative portfolios that represent different levels of success in implementation. Adaptive pathway approaches can also be used.
Ethical uncertainties	These can be addressed in an inclusive approach to goal setting and during the trade-off process.

Table 5
Features of RDM which assist policy makers articulate robust climate policy.

- **Begin from the end.** RDM encourages development of the analytical framework around the problem so as to ensure that policymakers' questions are answered. RDM - especially with adaptive planning (Haasnoot et al., 2013) - can identify and work with lead-in times (e.g. the lead time for BECCS development allowing policymakers to identify decision points);
- **Characterization of uncertainty.** The explicit acceptance of deep uncertainty ensures policymakers are not over-confident in modelling outputs. Rather, uncertainty is characterised as the degree to which the extent of uncertainty might affect proposed solution sets or the ability to realise objectives or indeed whether those objectives are relevant (Kahneman and Klein, 2009 and Klein, 2013);
- **Multi-objective Analysis.** An RDM analysis will typically range over several classes of factors to explore whereby multiple policymaking actors will be able to have their priorities accommodated for. This also allows the identification of low-regret solutions in the short term which satisfy multiple objectives, thus avoiding polarisation;
- **Iteration.** As analyses are inherently iterative, the accommodation of climate policy portfolios can be refined and complexity unpacked for policymakers over the course of analysis to ensure robustness under uncertainty; and
- **Accessibility and Transparency.** The forcing of RDM to share analytical output and insights allows for broader capacity for policymakers to have greater awareness of analysis.

RDM approaches therefore force an anthropological choreography which breaks the entrenched `tribal' axioms of the design of climate policy (Thompson, 1984). The iterative nature and underpinning philosophy of 'deliberation with analysis' makes for plurality of audience engagement, and therefore transparency, as well as the imposition of value sets which allow trade-offs to be identified in a clear manner. Understanding of modelling assumptions, auditability by different modelling communities, and integration of models in the policy development process would be extended beyond a small technical community as advocated by Strachan et al. (2016). Uncertainties and assumptions would be explicitly discussed and narratives co-generated between analytical and policymaking communities, in contrast to the narrower analytical communities and assumption sets behind IAM research. Additional benefits for policy makers will likely include: (1) better engagement of stakeholders in policy making; (2) a more robust suite of policy portfolios that address deep uncertainty around climate across a range of possible futures; (3) clearer understanding of which policy portfolios are likely to work and those vulnerable to exogenous factors; and (4) through iterative deliberation, outcomes are more likely to be accepted by stakeholders and therefore more likely to be implemented. This would be highly beneficial in policy design and decision making around the development of the post-Paris international climate agenda (Waisman et al., 2019). An RDM perspective would illuminate the fragility of the solution-chasing outputs which achieve 2 °C and 1.5 °C climate targets and force greater understanding of the need to be transparent, flexible and persistently aggressive in pursuit of mitigation (Pye et al., 2019 and Winning et al., 2018).

5. Conclusions

This paper was stimulated by our observation of the narrowness, fragility and opacity of the manner in which carbon dioxide removal, and especially BECCS, has become embedded in global mitigation pathways at a scale of multiple $GtCO_2$ per year as a function of the IAM optimisation approach, bypassing the societal debate that should have accompanied such recommendations. Recognising that the desire for answers that provide this “illusion of concreteness” is a systemic one, that pervades many modern institutions e.g. demonstrated in the World Banking systems by Kay and King, 2020. We show that the modelling philosophy underlying IAMs is ill-suited to exploring the deep uncertainty that pervades questions of long-term policy pathways and technology choice, and propose the use of alternative tools designed explicitly to characterise and manage such uncertainty.

We postulate that employing RDM (and similar) approaches can shift evidence provision to policy from a transactional process to a deliberative one, actually supporting difficult deliberations rather than proposing a fait accompli answer. For example, in CDR this might shift the debate from ‘*what is the optimal pathway to meeting climate targets under the most likely scenario?*’ to ‘*how can we develop a robust climate policy regardless of what happens?*’. By broadening participation in defining future scenarios and seeking vulnerabilities in prevalent assumptions, RDM can broaden the range of policy options considered and stimulate creativity in seeking robust pathways to meeting climate targets.

Specifically, we outline how this framework could support a deeper examination of the role of CDR in the light of the prominence of BECCS in IAM outputs. Developing effective and sustainable CDR policy is likely to require co-evolution and iterative refinement of policies as CDR efforts scale up over decades, in the context of public scrutiny and debate. RDM processes would facilitate this by making more explicit the issues in CDR development and implementation that are highly uncertain and sensitive to assumptions, which therefore need to be considered more carefully to identify near-term low-regret options to support technological development. For example, RDM can explicitly examine the vulnerabilities and lead times associated with BECCS and alternative CDR options, as well as the resource and value trade-offs involved (e.g. interactions between CDR and food systems). RDM can thus assist in understanding whether and how CDR should have a role in long-term climate policy, and what near-term steps are required to develop CDR approaches in a societally acceptable manner.

We present a case for the more widespread use of SFDA and RDM approaches within climate policy as a first step, rather than prescribing in substantive detail what issues RDM methods should focus on. To achieve the latter would require the broader adoption of RDM in the climate policy community at national and international level. This would require a deliberate and co-ordinated research effort accommodating experience from efforts to develop key technologies; participatory engagement with the public and stakeholders; open knowledge sharing sessions with industry, developers and civil society; and a range of activities including policy analysis, prototyping and engagement. This is a significant research effort requiring much wider participation. Elements of this research agenda will form the basis of additional research, with a view to realising the broader use of SFDA and RDM in climate policy development.

CRediT authorship contribution statement

Mark Workman: Conceptualization, Formal analysis, Resources, Supervision, Writing - original draft, Writing - review & editing, Project administration, Funding acquisition. **Geoff Darch:** Conceptualization, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Kate Dooley:** Conceptualization, Validation, Formal analysis, Writing - original draft, Writing - review & editing. **Guy Lomax:** Conceptualization, Validation, Formal analysis, Writing - original draft, Writing - review & editing. **James Maltby:** Conceptualization, Validation, Writing - original draft, Writing - review & editing. **Hector Pollitt:** Conceptualization, Validation, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare no conflict of interest.

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