Global Environmental Change 42 (2017) 107–116

Contents lists available at ScienceDirect

Global Environmental Change

journal homepage: www.elsevier.com/locate/gloenvcha

Understanding scientists' computational modeling decisions about climate risk management strategies using values-informed mental models

Lauren A. Mayer[a,*], Kathleen Loa[a], Bryan Cwik[b], Nancy Tuana[c], Klaus Keller[d,e], Chad Gonnerman[f], Andrew M. Parker[a], Robert J. Lempert[a]

[a] *RAND Corporation, United States*
[b] *Philosophy and University Studies, Portland State University, United States*
[c] *Department of Philosophy, Penn State University, United States*
[d] *Department of Geosciences, Penn State University, United States*
[e] *Department of Engineering and Public Policy, Carnegie Mellon University, United States*
[f] *Department of Philosophy, University of Southern Indiana, United States*

ARTICLE INFO

Article history:
Received 22 June 2016
Received in revised form 9 December 2016
Accepted 12 December 2016
Available online 27 December 2016

Keywords:
Values-informed mental models
Climate change
Risk management
Decision making under uncertainty

ABSTRACT

When developing computational models to analyze the tradeoffs between climate risk management strategies (i.e., mitigation, adaptation, or geoengineering), scientists make explicit and implicit decisions that are influenced by their beliefs, values and preferences. Model descriptions typically include only the explicit decisions and are silent on value judgments that may explain these decisions. Eliciting scientists' mental models, a systematic approach to determining how they think about climate risk management, can help to gain a clearer understanding of their modeling decisions. In order to identify and represent the role of values, beliefs and preferences on decisions, we used an augmented mental models research approach, namely *values-informed* mental models (ViMM). We conducted and qualitatively analyzed interviews with eleven climate risk management scientists. Our results suggest that these scientists use a similar decision framework to each other to think about modeling climate risk management tradeoffs, including eight specific decisions ranging from defining the model objectives to evaluating the model's results. The influence of values on these decisions varied between our scientists and between the specific decisions. For instance, scientists invoked ethical values (e.g., concerns about human welfare) when defining objectives, but epistemic values (e.g., concerns about model consistency) were more influential when evaluating model results. ViMM can (i) enable insights that can inform the design of new computational models and (ii) make value judgments explicit and more inclusive of relevant values. This transparency can help model users to better discern the relevance of model results to their own decision framing and concerns.

1. Introduction

Managing climate change risks pose nontrivial decision problems. A number of management strategies exist, but each has advantages and limitations, which impose both temporal and spatial tradeoffs between the potential objectives of stakeholders (e.g., Goes et al., 2011; Robock, 2008). Furthermore, climate/atmospheric behavior and climate management strategy impacts are rife with deep uncertainty (Keller et al., 2008; Vellinga et al., 2009; Weitzman, 2011) where decision makers disagree about the appropriate problem framing and how to characterize strategy tradeoffs (McInerney et al., 2012; Swart et al., 2009). This framing and characterization, though, is imperative for informing decisions about the design and implementation of strategies.

Climate risk management (CRM) strategies include variations of proactive and reactive plans including mitigation (e.g., increased deployment of renewable energy) adaptation (e.g., efforts to prevent flooding in coastal areas) and atmospheric geoengineering (i.e., injecting particles (or particle precursors) into the atmosphere

* Corresponding author at: RAND Corporation, 4570 Fifth Ave Suite 600, Pittsburgh, PA 15213, United States.
E-mail address: Lauren@rand.org (L.A. Mayer).

http://dx.doi.org/10.1016/j.gloenvcha.2016.12.007
0959-3780/

to cool the Earth's surface (Barrett, 2008)). Developing a decision framework for navigating the tradeoffs between such strategies may inform the design of computational models (referred to as models for the remainder of the paper) and decision tools that can analyze and clearly present these tradeoffs. Current analyses of CRM strategies include the use of Earth system models (Sherwood et al., 2014; Sriver et al., 2012), integrated assessment models (IAMs) (e.g., McInerney et al., 2012; Nordhaus, 2008), and robust decision making (RDM) analyses (e.g., Hall et al., 2012; Lempert et al., 2012). These models may take on many different designs and configurations depending on the assumptions made, for instance, about the processes determining the sign and magnitudes of climate feedbacks, economic and social factors that influence greenhouse gas emissions, the atmospheric chemistry and biogeochemical cycles controlling those emissions, and the impact of those emissions on the climate and, in turn, on humans. When developing such models, scientists (explicitly or implicitly) make decisions about how to characterize the relationships between these assumptions, in particular, how to represent uncertainty in those assumptions and the outcomes (i.e., output) of the model. These decisions are influenced by a number of factors including scientists' preferences, past experience and knowledge.

Understanding the decisions that drive the model designs is arguably important for the informed use of these tools. Typically, important aspects of these decisions are specified in the model description and documentation (see, for example, Nordhaus (2008), Lempert et al. (2012), McInerney et al. (2012), or Sriver et al. (2012)). These descriptions often focus on the explicit decisions and are often silent on arguably important implicit decisions. For example, model documentation usually discusses key model assumptions, but provide, at best, only a very brief discussion regarding *why* the scientist(s) chose a specific metric such as the expected value of the discounted utility of consumption or a specific reliability of achieving an objective (e.g., McInerney and Keller, 2008; McInerney et al., 2012). Characterizing scientists' "mental models," or how they think about the problem, has hence the potential to improve the understanding of both their explicit and implicit decisions.

A mental model is an internal representation of external reality that is thought to influence reasoning, cognition and decision making (Gentner and Stevens, 1983; Johnson-Laird, 1983). An individual's mental model includes their experiences, assumptions, beliefs, and biases about the world. In decision making, mental models include an individual's perception of a situation, decision contexts, features in the system, potential solutions and biases (Chermack, 2003). Mental models of a decision situation can be depicted visually as an influence diagram where decisions, and factors that influence those decisions, are shown as nodes, with arrows denoting the direction of influence between nodes (Morgan et al., 2002). This depiction allows for the systematic comparison between individuals' mental models, highlighting how people's thoughts about a decision (e.g., regarding climate risk management strategies) are similar or different.

One method for characterizing and comparing individuals' mental models is the Mental Models Approach (Morgan et al., 2002). While originally used to aid in the design of risk communication materials for the general public (e.g., Bruine de Bruin et al., 2009; Downs et al., 2004; Fleishman et al., 2010; Olson et al., 2011), the method has also been used to inform the development of computational models and decision tools for a variety of topics including low-carbon electricity (Mayer et al., 2014), nanoparticles (Morgan, 2005), infrastructure resilience (McDaniels et al., 2008), environmental risk management (Bridges et al., 2013) and flood risk management (Wood et al., 2012). In these applications, the factors that influence the decision being modeled (e.g., which low-carbon electricity or flood risk management strategy to implement) primarily include those related to attributes of the decision alternatives (e.g., costs and benefits of a strategy) or characteristics of the systems that may influence those attributes (e.g., human behavior, climate dynamics).

Scientists' values, or their disposition to form a normative attitude (Brennan et al., 2013), toward the factors that influence the decision being modeled are often ignored in the mental models used to inform computational models and decision tools. Values are traditionally treated as exogenous in the Mental Models Approach, essentially being "plugged in" to the factors and decisions after the fact (Morgan et al., 2002). However, individuals do not apply values uniformly to their decisions (e.g., Kahneman et al., 1998; Kahneman and Tversky, 2000). In fact, Bessette et al. (2016) showed that individuals' values related to CRM are applied differently depending on the strategy being evaluated. When values are actually considered within mental models, they usually only include a small subset of ethical values such as "priorities to protect public health/welfare . . . [and] environmentally sensitive areas" (Wood et al., 2012, p. 1357). Values can range, though, from well-articulated normative commitments to dispositional states that are unacknowledged by individuals (Diekmann and Zwart, 2014). For example, values related to CRM strategies for New Orleans have been shown to range from 'basic needs and survival' to 'sense of place' to 'stakeholder engagement' (Bessette et al., 2016).

Values play a central role in the development of computational models (Diekmann and Zwart, 2014; Fleischmann and Wallace, 2006; Wallace, 1994). As an illustration, a scientist who strongly values future generations (i.e., intergenerational justice) may develop a model that includes outcomes (e.g., costs and benefits) specific to future people, and long timescales that can accommodate such outcomes. This need for long time scales then can motivate the scientist to value models that are more parsimonious and easier to calibrate, compared to more complex models that include more processes, but have to rely more on expert judgments and are more difficult to calibrate (Oppenheimer et al., 2008). As a second example, consider the decision about the level of model complexity and resolution that climate modelers often face. Increasing the model complexity and/or resolution can enable an improved representation of processes but typically comes at the cost of a decreased number of feasible model evaluations. These value judgments also influence other factors scientists consider. As in the first example, values may influence *why* scientists include certain attributes of the decision alternatives (e.g., costs and benefits of a strategy) and characteristics of the systems (e.g., human behaviors) in their models. Users of decision support tools may not explicitly realize these value judgments.

Understanding *why* scientists think about the tradeoffs (e.g., between CRM strategies) the way they do may provide a window into the value judgments of the scientists who develop computational models and decision support tools. Such insights can help to inform the design of new models and tools that make these value judgments explicit. This transparency can allow decision makers who use these models and tools to better discern the relevance of model results to their own decision framing and concerns.

In this study, we use an augmented mental models research approach named values-informed mental models (ViMM) (Bessette et al., 2016) to capture how a set of scientists thinks about modeling CRM strategy tradeoffs and *why* – that is, how their values influence this thinking. ViMM includes an explicit focus on values in order to illustrate how they influence an individual's representation of the decision situation. Rather than assuming that values are only relevant once the problem has been identified and objectives have been clarified, ViMM recognizes that an