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Comparing Robust Decision-Making and Dynamic Adaptive Policy Pathways for model-based decision support under deep uncertainty

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ABSTRACT

A variety of model-based approaches for supporting decision-making under deep uncertainty have been suggested, but they are rarely compared and contrasted. In this paper, we compare Robust Decision-Making with Dynamic Adaptive Policy Pathways. We apply both to a hypothetical case inspired by a river reach in the Rhine Delta of the Netherlands, and compare them with respect to the required tooling, the resulting decision relevant insights, and the resulting plans. The results indicate that the two approaches are complementary. Robust Decision-Making offers insights into conditions under which problems occur, and makes trade-offs transparent. The Dynamic Adaptive Policy Pathways approach emphasizes dynamic adaptation over time, and thus offers a natural way for handling the vulnerabilities identified through Robust Decision-Making. The application also makes clear that the analytical process of Robust Decision-Making is path-dependent and open ended: an analyst has to make many choices, for which Robust Decision-Making offers no direct guidance.

1. Introduction

Uncertain changes in climate, technological, socio-economic and political situations, and the dynamic interaction among these changes, and between these changes and interventions, pose a challenge to planners and decision-makers. Due to these uncertainties, there is a risk of making an inappropriate decision (too little, too much, too soon, or too late). There is a need for approaches that assist planners and decision-makers with making long-term plans and informed policy decisions under deep uncertainty. Weaver et al. (2013) argue that exploratory model-based approaches are highly suitable for supporting planning and decision-making under deep uncertainty. In exploratory modeling, modelers account for the various unresolvable uncertain factors by conducting series of computational experiments that systematically explore the consequences of alternative sets of assumptions pertaining to the various deeply uncertain factors (Bankes, 1993; Bankes et al., 2013). A literature is emerging that adopts this exploratory modeling approach in support of decision-making under deep uncertainty (e.g. Auping et al., 2015; Bryant and Lempert, 2010; Dalal et al., 2013; Groves et al., 2014; Groves and Lempert, 2007; Hadka et al., 2015; Halim et al., 2016; Hall et al., 2012; Hallegatte et al., 2012; Herman et al., 2015; Kasprzyk et al., 2013; Kwakkel et al., 2013, 2015; Kwakkel and Pruyt, 2013, 2015; Kwakkel et al., 2012; Lempert, 2002, 2003; Lempert and Collins, 2007; Lempert and Groves, 2010; Maier et al., 2016; Matrosov et al., 2013a, 2013b; Parker et al., 2015; Pruyt and Kwakkel, 2014; Thissen et al., 2016). A substantial fraction of this literature focuses on model-based decision support for environmental systems undergoing change.

Over the last decade, climate adaptation research has increasingly focused on supporting decision-makers in developing climate adaptation strategies[1] and understanding the tradeoffs among different climate adaptation options (Maru and Stafford Smith, 2014). This research focus represents a shift from a focus on understanding climate change impacts to a solution-oriented focus on supporting climate adaptation decision-making through iterative risk management. Within the broader literature on decision-oriented climate adaptation, one strand of research has a strong

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[1] In this manuscript we use strategy, policy, policy option, and plan interchangeably.

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analytical focus on designing effective climate adaptation strategies in the presence of a wide variety of presently irresolvable deep uncertainties (Dessai and Hulme, 2007; Dessai et al., 2009; Lempert et al., 2003; Maru and Stafford Smith, 2014; Wise et al., 2014). Because of the presence of unavoidable uncertainty, decision-makers are advised to look for robust decisions that have satisfactory performance across a large range of plausible futures. One of the key design principles for such robust decisions is to make plans that are flexible and can be adapted over time in response to how the world actually unfolds (Haasnoot et al., 2012; Hallegatte, 2009; Kwakkel et al., 2010; Walker et al., 2013). The acceptance of uncertainty as an inevitable part of long-term decision-making has given rise to the development of new model-based tools and approaches. These include Dynamic Adaptive Policy Pathways (Haasnoot et al., 2013), Adaptive Policy-Making (Kwakkel et al., 2010), Real Options analysis (de Neufville and Scholtes, 2011; Woodward et al., 2014), Info-Gap Decision Theory (Ben Haim, 2006; Korteling et al., 2013), decision scaling (Brown et al., 2012; LeRoy Poff et al., 2015), Robust Decision-Making (Groves and Lempert, 2007; Lempert and Collins, 2007), and Many Objective Robust Decision-Making (Hadka et al., 2015; Herman et al., 2015; Kasprzyk et al., 2013).

The availability of a variety of model-based analytical approaches for designing flexible robust plans raises a new set of questions. How are the various approaches different? Where do they overlap? Where are they complementary? Answering these questions can help to pave the way for the future harmonization and potential integration of these various approaches. It might also help in assessing if certain approaches are more applicable in certain decision-making contexts than others. Hall et al. (2012) compare Info-Gap Decision Theory and Robust Decision-Making. They conclude that along quite different analytical paths, both approaches arrive at fairly similar but not identical results. Matrosov et al. (2013b) also compare Info-Gap and Robust Decision-Making. They reach a similar conclusion and discuss in more detail the complementary character of the analytical paths used by both approaches. Matrosov et al. (2013a) compare Robust Decision-Making with an economic optimization approach (UK Water Industry Research (UKWIR), 2002). In this case, the results are quite different, suggesting a need to combine both approaches. Roach et al. (2015, 2016) compare Info-Gap Decision Theory and robust optimization. They conclude that there are substantial differences between the plans resulting from these two approaches, and argue in favor of mixed methodologies. Gersonius et al. (2015) compare a real options analysis (in detail reported in Gersonius et al., 2013) with an adaptation tipping point analysis (Kwadijk et al., 2010). They highlight the substantial differences in starting points and suggest that both approaches could be applied simultaneously.

In this paper, we compare the Dynamic Adaptive Policy Pathways (DAPP) approach (Haasnoot et al., 2013) with Robust Decision-Making (RDM) (Groves and Lempert, 2007). The Dynamic Adaptive Policy Pathways approach has not been compared before with any of the other model-based analytical approaches. We choose to compare it with RDM as it has served as a benchmark against which other approaches have been compared. The aim of the comparison is to provide insight into the different analytical paths followed by the two approaches. What information and tools are needed, what decision relevant insights are being generated, and how different is the resulting plan emerging from the application of the two approaches? We compare both approaches using a stylized case, inspired by a river reach in the Rhine Delta of the Netherlands (Haasnoot et al., 2012).

From a conceptual point of view, RDM is an iterative process for developing a robust plan. Robust decision-making provides little guidance on how this robustness is to be achieved, resulting in some claims that RDM is intrinsically static. This claim, however, is at odds with various RDM applications that produce adaptive plans (e.g. Bloom, 2015; Groves et al., 2013, 2014). To provide guidance in the development of an adaptive plan using RDM, we draw on adaptive policymaking (Hamarat et al., 2013; Kwakkel et al., 2010). In contrast, the DAPP approach primarily emphasizes dynamic adaptation over time and specifies a stepwise approach for developing such plans. This stepwise approach is more open ended with respect to how models can be used in it. To do this, we draw on earlier work on the use of multi-objective robust optimization for the design of adaptation pathways (Kwakkel et al., 2015).

Given this setup, we can already highlight some key differences. Since RDM is an iterative process where one or more candidate plans are stress-tested over a range of uncertainties, the computational costs are primarily dependent on the number of plans that are tested and the number of cases needed to provide reliable insight into their vulnerabilities. In contrast, the multi-objective optimization approach exhaustively explores the design space and is, therefore, computationally more expensive. This implies also that in RDM the design space is not analyzed with the same rigor as in the multi-objective optimization approach.

In Section 2, we introduce both Robust Decision-Making and the Dynamic Adaptive Policy Pathways approach in more detail. In Section 3, we introduce the case to which both approaches are applied. Section 4 contains the Robust Decision-Making application, and Section 5 contains the Dynamic Adaptive Policy Pathways application. We compare the results in Section 6. Section 7 presents the conclusions.

2. Background on Robust Decision-Making and Dynamic Adaptive Policy Pathways

2.1. Robust Decision-Making

There are four main steps in RDM, as shown in Fig. 1. The first step is a generic policy analytic decision structuring activity that aims at conceptualizing the system under study, and identifying the key uncertainties pertaining to this system, the main policy options, and the outcomes of interest. This step often involves stakeholder interaction. The second step is case generation. In this step, the behavior of one or more models of the system under study is systematically explored across the identified uncertainties, and the performance of candidate strategies is assessed. The third step is scenario discovery (Bryant and Lempert, 2010). Using statistical machine learning algorithms, the performance of candidate strategies across the generated cases is analyzed to reveal the conditions under which candidate strategies perform poorly. These conditions reveal vulnerabilities of the strategies, in light of which they can be modified. Step two and three together are sometimes also referred to exploratory modeling (Bankes et al., 2013). The fourth step is trade-off analysis, in which the performance of the different strategies is compared across the different outcome indicators, thus providing an additional source of information that can be used in redesigning the strategy. The steps can be iterated until a satisficing robust strategy emerges.

Scenario discovery forms the analytical core of RDM (Bryant and Lempert, 2010; Groves and Lempert, 2007). The main statistical rule induction algorithm that is used for scenario discovery is the Patient Rule Induction Method (PRIM) (Friedman and Fisher, 1999). PRIM aims at finding combinations of values for the uncertain input variables that result in similar characteristic values for the outcome variables. Specifically, PRIM seeks a set of subspaces of the uncertainty space within which the value of a single output variable is considerably different from its average value over the entire domain. PRIM describes these subspaces in the form of hyper