Environmental Modelling & Software 81 (2016) 154–164

Contents lists available at ScienceDirect

Environmental Modelling & Software

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

# An uncertain future, deep uncertainty, scenarios, robustness and adaptation: How do they fit together?

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ARTICLE INFO

*Article history:*
Received 23 December 2015
Received in revised form
30 March 2016
Accepted 30 March 2016
Available online 12 April 2016

*Keywords:*
Uncertain future
Deep uncertainty
Scenarios
Robustness
Adaptability
Decision support

ABSTRACT

A highly uncertain future due to changes in climate, technology and socio-economics has led to the realisation that identification of "best-guess" future conditions might no longer be appropriate. Instead, multiple plausible futures need to be considered, which requires (i) uncertainties to be described with the aid of scenarios that represent coherent future pathways based on different sets of assumptions, (ii) system performance to be represented by metrics that measure insensitivity (i.e. robustness) to changes in future conditions, and (iii) adaptive strategies to be considered alongside their more commonly used static counterparts. However, while these factors have been considered in isolation previously, there has been a lack of discussion of the way they are connected. In order to address this shortcoming, this paper presents a multidisciplinary perspective on how the above factors fit together to facilitate the development of strategies that are best suited to dealing with a deeply uncertain future.


## 1. Introduction

Uncertainty has been considered extensively in the context of environmental and hydrological models for many years (Ascough et al., 2008; Durbach and Stewart, 2012; Refsgaard et al., 2007; Stewart, 2005). Approaches to dealing with uncertainty generally consider uncertainties in model inputs, model parameters, and model structure by way of probability distributions, resulting in a distribution of outputs around some "best-guess". However, when faced with an uncertain future as a result of drivers such as climate, technological, socio-economic and political change, and corresponding policy and societal responses, the assumption that we can identify a "best-guess" output in the first place might no longer be appropriate (Haasnoot and Middelkoop, 2012; Walker et al., 2013a). This is because in such situations, there are multiple plausible future trajectories that generally correspond to distinct future states of the world that do not have an associated probability of occurrence or cannot even be ranked (Kwakkel et al., 2010). Consequently, when dealing with an uncertain future, a different conceptual approach to thinking about uncertainty is needed, which has resulted in the development of different terms that can be used to encapsulate the concept of multiple plausible futures, of which *deep uncertainty* (Lempert et al., 2003; Walker et al., 2013b) is arguably the most well-known.

Thinking about future uncertainty in terms of *multiple plausible futures*, rather than probability distributions, has implications in terms of the way uncertainty is quantified or described, the way system performance is measured and the way future strategies, designs or plans are developed. In terms of uncertainty quantification, consideration of *multiple plausible futures* generally necessitates the development of *scenarios* (e.g. Bárcena et al., 2015; Beh et al., 2015b; Gal et al., 2014; Greiner et al., 2014; Lan et al., 2015; Paton et al., 2013), rather than just sampling from probability distributions. In relation to system performance measurement, the presence of multiple plausible futures that cannot be characterised by probability distributions requires consideration of performance measures such as *robustness* (e.g. Kasprzyk et al., 2013; Matrosov et al., 2013; Mortazavi-Naeini et al., 2015; Paton et al., 2013;

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http://dx.doi.org/10.1016/j.envsoft.2016.03.014
1364-8152/

Whateley et al., 2014), which reward strategies, designs or plans that perform well under a range of future conditions, rather than performance measures that consider the probability of acceptable system performance for a "best-guess" future, such as reliability. When it comes to the development of future strategies, designs or plans, these generally need to be robust over long periods of time, making *adaptive strategies* (Beh et al., 2015a; Groves et al., 2014; Haasnoot et al., 2013, 2014; Hamarat et al., 2014; Lempert and Groves, 2010; Ray et al., 2011) a viable alternative to their more commonly used static, fixed counterparts.

While each of these elements (i.e. thinking of future uncertainty as being represented by *multiple plausible futures*, using *scenarios* to quantify uncertainty, using *robustness* to measure system performance, and considering *adaptive strategies* as viable alternatives to fixed strategies) is not new in itself, they have generally been considered in isolation. This is exemplified by a number of recent synthesis papers, which have primarily focussed on one of these elements, without considering their connections. For example, Herman et al. (2015) mainly focus on measures of robustness, while Kwakkel et al. (2016a) and Dittrich et al. (2016) highlight different approaches to developing future strategies. While there are a number of review papers on scenarios (Bradfield et al., 2005; European Environmental Agency, 2009; Haasnoot and Middelkoop, 2012; Van Notten, 2005; Van Notten et al., 2005), and several examples of quantifying multiple plausible futures using scenarios (Fortes et al., 2015; Vervoort et al., 2014; Kok and Van Delden, 2009; Van Delden and Hagen-Zanker, 2009), recognition of these types of scenarios and their relevance for the quantification of multiple plausible futures have generally not featured in papers on deep uncertainty. Consequently, there is a need for a paper that offers a synthesis of how these elements fit together in the context of dealing with multiple plausible futures.

In order to address this shortcoming, the primary objective of this paper is to provide a multidisciplinary perspective on how the concepts of an *uncertain future*, *deep uncertainty*, *scenarios*, *robustness* and *adaptation* fit together to facilitate the development of strategies, designs and plans that are best suited to dealing with an uncertain future. The remainder of this paper is organised as follows. An outline of different paradigms for modelling the future is given in Section 2, followed by the articulation of some of the terms that encapsulate the concept of multiple plausible futures in Section 3. A classification of scenario types is given in Section 4, along with a discussion of their suitability for quantifying multiple plausible futures. A categorisation of the two main approaches to developing strategies for dealing with future uncertainties, as well as a discussion of the conditions that favour each of these approaches, is given in Section 5, followed by a discussion of the implications of considering multiple plausible futures on modelling in Section 6. Finally, a summary and concluding remarks are presented in Section 7.

## 2. Three complementary paradigms for modelling the future

A fundamental purpose of modelling is to help understand the future, to support planning or adaptation. We focus here on quantitative models defined by a model structure and a set of parameter values. The model is applied to input data in order to obtain estimates of future system states. The models therefore have some temporal element (even if they do not generate time series), and are usually spatially situated (even if they are not spatially distributed). The quantitative model is usually linked with an underlying qualitative conceptual model (Argent et al., 2016), which provides a more complete, but less precise picture of the system. A particular future can be described by its state, but also by the model structure, parameters and inputs in which that state occurs.

The need to address uncertainty in modelling and the existence of different types of uncertainties is widely recognised. Uncertainties are generally differentiated according to their different levels, nature, and source (Ascough et al., 2008; Courtney, 2001; Guillaume et al., 2012, 2015; Kwakkel et al., 2010; Refsgaard et al., 2007; Walker et al., 2003; Van Asselt, 2000). A continuum of levels of uncertainty, ranging from determinism to total ignorance (Kwakkel et al., 2010; Walker et al., 2003, 2010), includes the idea that information about outcomes and probabilities is often not known (see also Brown, 2004), such that there is a need to deal with "Knightian" uncertainty, rather than probabilistic risk (Knight, 1921). In terms of the nature of uncertainty, a classic distinction is between aleatory or ontic uncertainty, and epistemic uncertainty (Hacking, 2006; Hoffman and Hammonds, 1994). Aleatory uncertainty is the intrinsic uncertainty of natural variability. Epistemic uncertainty can arise due to a lack of knowledge, or due to ambiguity. Ambiguity in this context means that there exist multiple frames of reference about given phenomena (Brugnach et al., 2008; Dewulf et al., 2005). Sources of uncertainty have commonly referred to model structure, data, and parameters. These typologies emphasise properties of the problem, which these previous studies have linked to a variety of suitable actions.

In the end, it is the action that matters, rather than the motivation. In terms of modelling the future, we consider that the actions addressing all these differences in types of uncertainty boil down to three complementary paradigms of how modellers conceptualise the future. These paradigms are defined based on sharp changes in mindset that occur when transitioning between them. The same problem can often be approached with any of the three paradigms, regardless of the inherent type of uncertainty. At the same time, the three paradigms are also usually used in combination, addressing different parts of a problem. As described below and summarised in Fig. 1, the three paradigms are: use of best available knowledge, quantification of future uncertainty, and exploring multiple plausible futures.

In the first paradigm, models are used to consolidate best available knowledge (Bankes, 1993), capturing the processes and

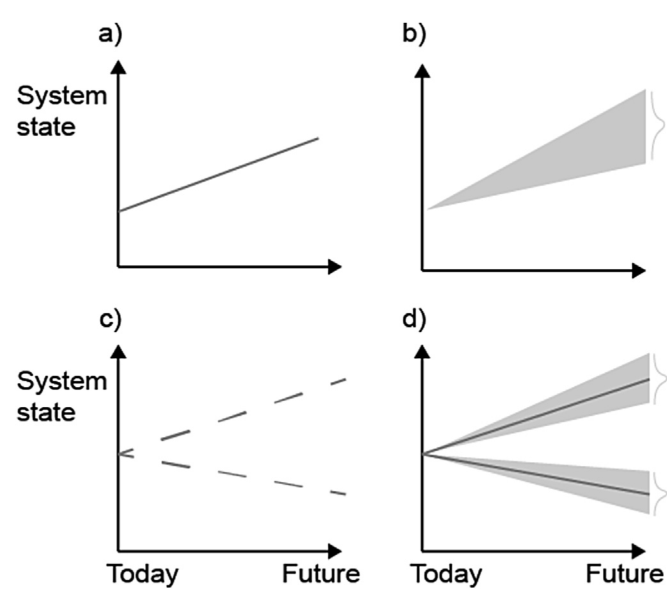


**Fig. 1.** Estimates of future system states according to different complementary paradigms for modelling the future: a) anticipating the future based on best available knowledge, b) quantifying future uncertainty, c) exploring multiple plausible futures, d) combining the three paradigms to address different sources of uncertainty within a problem. (Adapted from Mejia-Giraldo and McCalley (2014)).