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

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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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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

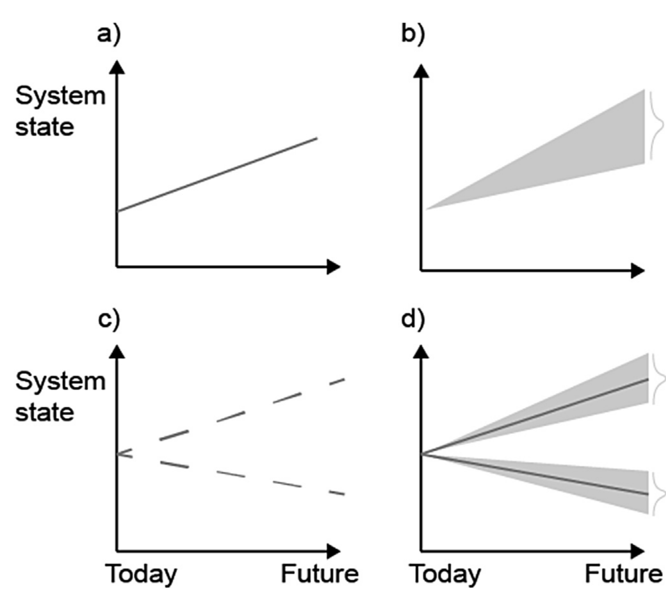

Fig. 1. Estimates of future system states according to different complementary paradigms for modelling the future: a) anticipating the future based on best available knowledge, b) quantifying future uncertainty, c) exploring multiple plausible futures, d) combining the three paradigms to address different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

conditions that allow us to anticipate a system's future behaviour. The idea is that knowledge can be gradually improved by further research and data collection. If surprises are encountered, like the discovery of black swans (Taleb, 2010), the model is altered to include new processes, notably capturing understanding of how transitions might occur within a system (Halbe et al., 2015). The idea of building up knowledge over time is powerful, but also has limitations. Philosophically speaking, models are unavoidably always incomplete (Oreskes et al., 1994). Some processes will always be missing, and in complex, adaptive systems small changes can have quite large, system wide effects. Practically speaking, improving models takes time and requires information that may not yet be available (see Bowden et al., 2012). Nevertheless, a model based on the best available knowledge might be used to produce a single estimate of the future, as in Fig. 1a. This corresponds to the idea of a clear enough or deterministic future (Walker and Haasnoot, 2011; Walker et al., 2003, 2010).

In the second paradigm, the future is treated as quantifiably uncertain in order to deal with system processes and conditions that are considered insufficiently well-known to be captured within models. Natural variability in inputs can be expressed as distributions (Beyer and Sendhoff, 2007; Birge and Louveaux, 2011) and the effect of measurement error in observations when estimating parameters is taken into account by specifying properties of the errors, notably in terms of a likelihood function (Schoups and Vrugt, 2010). This paradigm also extends to model structure (Gupta et al., 2012), for example by combining posterior distributions using Bayesian model averaging (Hoeting et al., 1999). When making predictions, modellers can therefore propagate uncertainty in inputs, parameters and model structures in order to obtain an estimate of uncertainty in outputs. The modelled process is assumed to be stationary, meaning that its statistical properties do not change over time (Koutsoyiannis and Montanari, 2015), and the conditions to which a system is subjected appear to "fluctuate within an unchanging envelope of variability" (Milly et al., 2008). The propagated uncertainty in system state may, however, be quite large and vary over time, often with larger uncertainty further in the future (Mahmoud et al., 2009), as shown in Fig. 1b. By using multimodal probability distributions, quantifying uncertainty even allows very different outcomes to be unified within a single plausible, though uncertain, future. This corresponds to a level of uncertainty characterised as "statistical" or probabilistic (Walker and Haasnoot, 2011; Walker et al., 2003, 2010).

The third paradigm explores *multiple plausible futures*, allowing the modeller to avoid the idea of a single (uncertain) future. This can be useful when the different processes and conditions seemingly do not easily fit within a single model, and their resulting futures cannot be harmonised within a probabilistic framework. Dynamics of change are not sufficiently known to be represented within a model, perhaps because future system behaviour is affected by processes for which data have not been or cannot be observed. However, the resulting systems and futures might still be described, including their dynamics. Knowledge is no longer consolidated within the model itself, but rather in the broader analytical context within which the model is used. This has been referred to as 'exploratory modelling' (Bankes, 1993; Bankes et al., 2001; Bankes et al., 2013), wherein each model realisation simply describes a "what-if" scenario, such that the result is conditional on its assumptions. As shown in Fig. 1c, the corresponding futures are treated as distinct, each with their own envelope of variability. This includes two commonly recognised levels of uncertainty, the first being "scenario uncertainty" or "a multiplicity of plausible futures", and the second being "recognised ignorance" or an "unknown future" (Walker and Haasnoot, 2011; Walker et al., 2003, 2010). Both cases are underpinned by the idea that no probabilities can be placed on the future, but that the uncertainty the latter deals with is in addition unbounded – we know that not all outcomes are known (Refsgaard et al., 2007). It is this kind of uncertainty that needs to be considered when dealing with a highly uncertain future as a result of climate, technological, socio-economic and political change and it is therefore the primary focus of this paper.

3. Terms used to encapsulate the concept of multiple plausible futures

There are different terms that can be used to encapsulate the concept of multiple plausible futures. In this paper, three of these will be discussed, including *"deep" uncertainty, "global/local" uncertainty* and *"VUCA" (Volatility, Uncertainty, Complexity and Ambiguity)*. These three terms appear to have evolved more or less independently and are therefore of interest for illustration purposes and are used to highlight that the issue of dealing with multiple plausible futures is gaining prominence in different disciplinary areas. This list is, however, by no means exhaustive.

The first term encapsulating the concept of multiple plausible futures is *deep uncertainty*, which has arguably received most attention in the environmental and water resources literature in recent years. Deep uncertainty arose in the context of model-based decision aiding and is by definition "the condition in which analysts do not know or the parties to a decision cannot agree upon (1) the appropriate models to describe interactions among a system's variables, (2) the probability distributions to represent uncertainty about key parameters in the models, and/or (3) how to value the desirability of alternative outcomes" (Lempert et al., 2003; Walker et al., 2013b). Hallegatte et al. (2012) further state that deep uncertainty may occur due to the presence of "(1) Knightian uncertainty: multiple possible future worlds without known relative probabilities; (2) multiple divergent but equally-valid world-views, including values used to define criteria of success; and (3) decisions which adapt over time and cannot be considered independently." A consistent, but slightly different definition of deep uncertainty is offered by Kwakkel et al. (2010), who define deep uncertainty in model-based decision support as the situation where the analyst is able to enumerate a variety of possibilities (e.g. futures, model formulations) without being able or willing to (rank) order these possibilities in terms of their perceived likelihood, as illustrated in Fig. 1c.

The second term encapsulating the concept of multiple plausible futures is "*global/local*" *uncertainty* (Mejia-Giraldo and McCalley, 2014), which was developed for the purpose of flexible infrastructure planning in the electricity sector. Global uncertainties result in significantly different trends in solutions, and therefore represent multiple plausible futures, as shown in Fig. 1c. Local uncertainties result in the envelope of uncertainty that surround a particular future, as shown in Fig. 1b. It should be noted that global and local uncertainty are classified in accordance with the effect they have on the solutions or strategies being developed, rather than the uncertain drivers or inputs, and therefore only make sense in a specific decision-making context.

The third term considered is *VUCA* (Volatility, Uncertainty, Complexity and Ambiguity), which is growing in prevalence in the business literature and originates from US Military College teachings (Bennett and Lemoine, 2014; Whiteman, 1998). *Volatility* can be considered as either the deviation from the expected or predicted mean, and a representation of heteroscedasticity (linked to local uncertainty – Fig. 1b), or the occurrence of extreme events/discontinuities in a future projection (Modarres and Ouarda, 2013; Syud et al., 2009; Van Notten et al., 2005). *Uncertainty*, which is closely related to the first condition of the definition of deep uncertainty, considers the unknown range of parametric inputs and also the impact of future or 'global' trends, as shown in Fig. 1c (Refsgaard et al., 2007; UKCIP, 2003; Walker et al., 2003). *Complexity* arises when links between an intervention and an impact are difficult to identify and quantify. High degrees of complexity are common in environmental management and decision-making and this can be closely related to the second condition of deep uncertainty and in reference to multiple plausible futures, where the casual relationships between factors may change in both structure and magnitude (Fig. 1c). Lastly, *ambiguity* in environmental management can be significant when different stakeholders hold differing beliefs on the level of uncertainty present, the causal relationships and also the preference of management solutions (Dewulf et al., 2005). Ambiguity challenges both the ability to predict the impact of interventions and, ultimately, what the preferred option is. This links well with the third condition of deep uncertainty and poses similar challenges for management in light of an uncertain future. A potential advantage of VUCA is that it can help in fostering a shared understanding between modellers and policy makers.

4. Methods for identifying multiple plausible futures

Arguably the most common approach to the identification of multiple plausible futures, or "states of the world" as they are referred to by Herman et al. (2015), is the use of *scenarios*. Mahmoud et al. (2009) defined scenarios as "possible future states of the world that represent alternative plausible conditions under different assumptions" and Van Notten et al. (2005, 2003) defined scenarios as "coherent descriptions of alternative hypothetical futures that reflect different perspectives in past, present and future developments, which can serve as a basis for action." Therefore, based on the above definitions, scenarios that are used to represent multiple plausible futures are generally not developed just by sampling from different variables over defined ranges, as they represent coherent storylines and have to be based on different assumptions about the future. Consequently, it is important to be aware of different types of scenarios, as, although all of them consider the future, they do so in different ways and are therefore not equally well suited to representing multiple plausible futures. Scenarios can be categorised based on the types of questions they are trying to answer (Börjeson et al., 2006), as shown in Fig. 2.

Predictive scenarios can be used to answer the question "what will happen?", for example, "*what will the environmental impacts of a development in area X be?"* This can be achieved using either "*Trend*" or "*What-if*" scenarios. "Trend" scenarios are a common approach to future planning, and can consist of a baseline or Business as Usual (BAU) scenario with slight variations from this baseline. BAU projecting assumes current conditions will continue, building from a historical trend and allowing for the impact of known policies. BAU scenarios are often used or adapted into a most likely scenario or a more neutral reference scenario against which the implications of decisions can be assessed and can therefore be considered to consolidate existing knowledge (Fig. 1a). Adding variance to this baseline creates scenarios that can be thought of as adding local uncertainty to BAU, most-likely or reference scenarios (Fig. 1b). This is commonly achieved by the addition of a low, medium, and high projection into the future deviating from the historical values.

Alternatively, "what-if" scenarios, which consider the future based on what will happen if a specific event occurs, altering the likely path, are another form of predictive scenario. For example, this type of scenario could be used to predict what will happen to society if a rapid high density residential development, a slower paced low-medium density housing precinct, or a technology hub is implemented.

Explorative or *exploratory* scenarios can be used to answer the question "what could happen?" For example, an exploratory scenario process could be used to answer the question "*what could influence sustainable development goals over the century?"*, with potential scenarios considering either a world of growing distrust in international organisations due to migration and military tension or one where societal will drives political action sparking a global, accepted approach to dealing with challenges. Exploratory scenarios have similarities with "what-if" scenarios, but consider longer time-frames and multiple perspectives.

Börjeson et al. (2006) categorise exploratory scenarios based on the influence of interested parties: *external* exploratory scenarios are characterised by the development of external factors beyond the control of the interested parties, while *strategic* scenarios consider what could happen if the interested parties act in a particular way. Consequently, the former do not consider policy options, while the latter do. However, in this paper, we propose a categorisation of exploratory scenarios based on whether they are *framed* or *unframed* during their development. Framing scenarios provides a scaffold for their development, in contrast to more organic scenario construction, which makes no prior assumptions about form. The development of *framed* scenarios is constrained by the consideration of particular driving forces or outcomes. While this provides guidance for their development, it also limits the breadth of the plausible futures that can be explored. Framed scenarios fall into two categories, those that are *framed on system uncertainties* and those that are *framed on outcomes*. Consequently, the latter can be considered as 'solution-focused' approaches, while the former can be considered as 'problem-focused' approaches, as they are not constrained by a particular decision context.

A well-known 'problem-focused' framework for the development of framed scenarios is the scenario logic approach (Schwartz, 1996), where typically a 2×2 matrix is produced by placing two

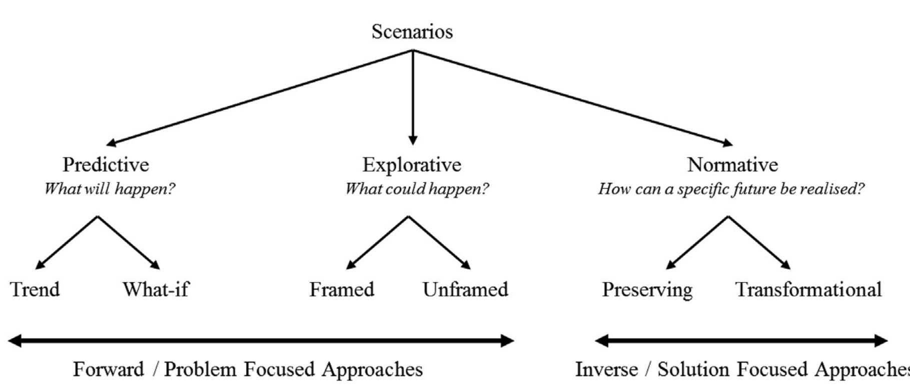

Fig. 2. Scenario classification (Adapted from Börjeson et al. (2006)).

key (uncertain) driving forces on the vertical and horizontal axes (Ramirez and Wilkinson, 2014; Van 't Klooster and Van Asselt, 2006; Van Asselt, 2012). This allows each scenario to be clearly differentiated from others and hence more easily communicated and understood. A similar approach, but focused on the development of 'solution-focused' framed scenarios, places "outcomes of interest" on the vertical and horizontal axes, rather than drivers, as in the 'problem-focused' approach (O'Neill et al., 2014). There are also several other ways of framing scenarios in higher dimensions, such as the combination of framed scenarios considering different factors of interest, including the combination of representative concentrations pathways (RCPs), shared socio-economic pathways (SSPs) and shared policy assumptions (SPAs) (Van Vuuren et al., 2014).

In contrast to framed scenarios, *unframed* scenarios are completely open in the way they formulate the factors, actors, and sectors included in their development, as well as their directions for change, and therefore have a greater ability to identify a wider range of multiple plausible futures. However, they are still constrained by the mental models and human cognitive limitations of the individuals involved in their development (Lempert et al., 2003; Sterman, 1994).

Unframed scenarios are commonly developed through intake of significant information via a combination of participatory processes, expert elicitation and extensive literature review, but do not consider pre-determined drivers or outcomes of interest as the starting point, as is the case with framed scenarios. This type of exploration can be traced to the scenario analysis techniques employed by Shell (Van der Heijden, 2011). They allow those constructing the scenarios to include any uncertainty, driver or thought and consider its impact on the future. An example of this type of scenario development can be seen in Kok et al. (2006b, 2006a) and Rotmans et al. (2000). Another example of developing unframed scenarios is the Perspectives model, which is based on cultural theory (Thompson et al., 1990) and has been used to develop a set of coherent, integrated scenarios describing climate and socio-economic developments and values seen from different worldviews (Hoekstra, 1998; Middelkoop et al., 2004; Rotmans and De Vries, 1997).

Normative scenarios can be used to answer the question "*how can a specific target be met*?" They have explicit starting points in the future regarding conditions or objectives to be met. Normative scenarios contain actions or steps that are required to achieve the desired objectives or future conditions to be realised. This can be useful for comparing potential actions or steps for achieving the future conditions (Parker et al., 2015). For example, a normative scenario may begin with the question "*how can electricity access across India be achieved*?" Scenarios may include pathways of dependence on fossil fuels and capital investments in network infrastructure, or improvements in battery technology, precipitating the roll out of renewable energy and micro-grids. Normative scenarios can be further categorised based on whether the desired outcomes are able to be achieved within the existing system structure, as is the case with "preserving" scenarios, or whether the existing system structure needs to be changed ("transformed"). Consequently, the focus of *preservative* scenarios is on how the desired target can be achieved as efficiently as possible, while the focus of *transformative* scenarios is on what changes have to be made to the system to enable the target to be met.

There are also differences between the types of scenarios based on the way they are generated. As can be seen in Fig. 2, predictive and explorative scenarios can be thought of as "*forward*" or "*problem-focused*" approaches to identifying future conditions of interest (Jones, 2012; Parker et al., 2015), as they consider the future by looking forward and exploring a variety of factors that influence the problem under consideration. In contrast, normative scenarios can be considered as "*inverse*" or "*solution-focused*" approaches to identifying future conditions of interest, as they usually work backwards from a desired target and place an emphasis on actions or solutions to either transform or preserve (Dessai and Hulme, 2007; Wilby and Dessai, 2010).

Although predictive, explorative, and normative scenarios all consider the future, they are not equally suited to identifying multiple plausible futures. In general, forward focused approaches have a greater ability to consider alternate multiple plausible futures, as described in Fig. 1c and d. However, as shown conceptually in Fig. 3, the degree to which forward approaches, including trend, what-if, framed and unframed scenarios, can explore multiple plausible futures can vary considerably.

As *trend* scenarios aim to forecast development, they offer limited ability to explore multiple plausible futures. As such, they are best suited to application to systems that are 'relatively well-known and well-defined' (Van Vuuren et al., 2012). They generally capture a limited system state and capture minimal divergence, similar to Fig. 1b. Similarly, What-if scenarios capture a limited range of system states, but can be used to assess well-known systems and the impacts of known options or uncertainties. If the divergence in plausible futures is minimal, what-if scenarios can capture futures, as shown in Fig. 1c and d.

Explorative scenarios are well suited to identifying multiple plausible futures, as they offer rich descriptions of future systems and look to incorporate qualitative and quantitative assumptions for alternate world views (Rounsevell and Metzger, 2010). These assumptions can involve diverse ideas and opinions. A broad array of techniques can be used for their development, although they commonly revolve around aspects encapsulated by changes to societal, technological, environmental, economic and political (STEEP) factors (Bradfield et al., 2005; Rounsevell and Metzger, 2010). This allows for various factors to be included in the description of future worlds and subsequently better encapsulates future uncertainty.

Framed exploratory scenarios capture divergent plausible futures, as shown in Fig. 1c and d, although *unframed* scenarios not constrained by predefined factors or driving uncertainties are capable of capturing a greater range of future system states. Framing scenarios on solution-focused axes allows for the targeting of uncertainties most relevant to the problem definition, while framing on uncertainties of the problem allows for a broader exploration of the selected factors or drivers.

Choosing whether to frame a set of scenarios or not and then

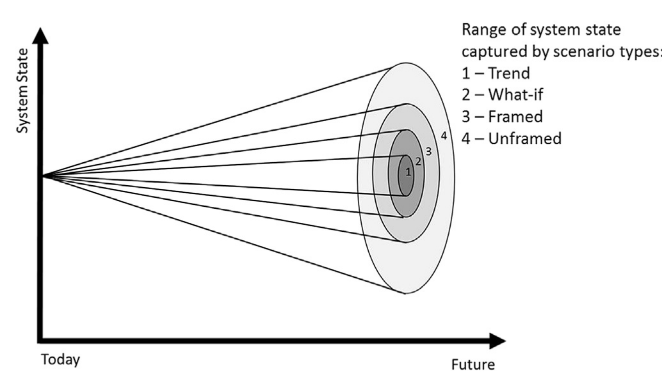

Fig. 3. Forward-focused scenario types encapsulating increasing variation in system state, allowing for more uncertain and divergent futures to be considered. Scenarios are considered as pathways from today to the future, or points in the future.

subsequently how to frame them, either on uncertain drivers or outcomes of interest, should be based on problem context. For more applied policy assessment, framing on outcomes may provide a more effective scenario development process. However, if the exploration and understanding of future uncertainty is of more significance, framing based on drivers or the use of unframed scenarios can provide a better platform for identifying multiple plausible futures. There are also instances when increased exploration is not necessarily of benefit to the scenario and overall decision support process. These situations may relate to physical constraints, and as such, applying constraints to the scenario frames or developing predictive scenarios may be more appropriate.

For *normative preservative* scenarios, quantitative methods for assessment are well suited to identifying conditions under which a target or system requirement can or cannot be met. Such approaches include scenario discovery (Bryant and Lempert, 2010; Groves and Lempert, 2007; Guivarch et al., 2016; Kwakkel and Jaxa-Rozen, 2016; Lempert, 2013; Lempert et al., 2008), decision scaling (Brown et al., 2012; Poff et al., 2015) and adaptation tipping point approaches (Kwadijk et al., 2010). For *normative transforming* scenarios, techniques such as backcasting (Kok et al., 2011; Vervoort et al., 2014) are most suitable, as they allow parties to work back from the unachievable target, stepping through the required actions that would enable its achievement.

In summary, the degree of exploration required is dependent on the system state, and the degree it is impacted by multiple plausible futures. This affects the type of scenario deemed appropriate to scope future changes, and there may be an emphasis on scoping or decision making influencing the choice between forward and inverse looking approaches. These scenarios, once conceived, are then used to assist in model-based decision support, allowing for a conceptualisation of the variability in system state, and as such, what future conditions developed strategies, designs or plans could be exposed to.

5. Coping with multiple plausible futures in model-based decision support

The aim of model-based decision support in the face of multiple plausible futures is to assist with the development of strategies, designs or plans (referred to as strategies hereafter) that perform adequately, irrespective of which of these futures actually occurs. This results in *robust outcomes*, where robustness can be thought of as a measure of the insensitivity of the performance of a given strategy to future conditions. This can be achieved by adopting two conceptually different approaches.

The first is a *static* approach, as part of which a *single, fixed* strategy is developed that performs adequately under as many plausible futures as possible. It should be noted that such a strategy can consist of one or a number of individual solutions or actions (referred to as solutions hereafter), and that these can occur simultaneously or be staged over the planning horizon of interest (e.g. Beh et al., 2015b). Static approaches often use one or two endpoint scenarios, describing a static point in the future.

The second is an *adaptive* approach, as part of which *multiple, flexible* strategies are developed that are tailored to different future conditions, with the option to switch between them over the length of the planning period in response to increased knowledge about the state of the world. Consequently, these multiple strategies can be thought of as providing adaptive pathways for responding to different plausible futures (e.g. Beh et al., 2015a, b; Haasnoot et al., 2013; Haasnoot et al., 2012). Adaptive approaches can either be static or dynamic. As part of static adaptive approaches, a basic policy remains fixed and contingency actions are taken to stay on course (e.g. Walker et al., 2001) or a set of adaptive pathways remains fixed over the length of the planning horizon, although there are opportunities to move between them (e.g. Kang and Lansey, 2014). As part of dynamic adaptive approaches, the actual pathways can also change over time as new knowledge about future states of the world becomes available (e.g. Beh et al., 2015a; Wise et al., 2014). Dynamic or adaptive approaches require the use of time series or transient scenarios, describing changing conditions over time (Beh et al., 2015a; Haasnoot et al., 2015).

It should be noted that as part of the static approach, the fixed, individual strategies are designed to be robust, so that the adequacy of their performance is insensitive to which future conditions occur. In contrast, as part of the adaptive approach, *individual strategies* are not necessarily robust, as they are tailored to particular plausible futures. However, the *overall outcome* is robust, as the strategies that are most appropriate for particular future conditions can be selected adaptively over time. Consequently, the use of adaptive approaches results in the *collective robustness* of the various strategies considered, rather than the *individual robustness* of a particular strategy.

The robustness of *individual strategies* that form part of static or adaptive approaches can be quantified based on expected values or other moments characterizing the distribution of outcomes, satisficing criteria, or measures based on regret (Giuliani and Castelletti, 2016; Herman et al., 2015; Kwakkel et al., 2015, 2016b; Lempert and Collins, 2007). In the context of the development of strategies that perform adequately in the face of multiple plausible futures, robustness measures based on the concept of satisficing appear to be the most appropriate. These robustness measures generally fall into two broad categories (Herman et al., 2015), including those that attempt to quantify the plausible futures under which a strategy performs adequately and those that attempt to quantify how far future conditions need to deviate from an expected future state before a strategy fails to perform adequately. Consequently, measures that belong to the latter category, such as Info-Gap (Ben-Haim, 2006), are likely to be less well suited to dealing with highly uncertain futures, as the expected, or “best-guess”, future state from which to deviate is unlikely to be known in such cases. This is because different scenarios are all plausible and to not have an associated probability or cannot be ranked, making it impossible to determine what the expected “best-guess” future conditions actually are, as discussed in the Introduction.

The plausible states used in the calculation of the former measure can be identified using some of the techniques for scenario development discussed in Section 4. When forward/top-down scenarios are used to identify multiple plausible futures, a common measure of robustness is the fraction of the scenarios under which a strategy performs adequately (Beh et al., 2015a; Herman et al., 2015; Paton et al., 2014a, 2014b; Van Vliet and Kok, 2015). When inverse/bottom-up scenarios are used as the basis for identifying multiple plausible futures, rather than starting with plausible futures as represented by discrete scenarios, the focus is on the identification of the model parameters and/or system states under which a solution performs adequately or better than an alternative solution. Consequently, in this case, robustness is a measure of the extent of these parameter spaces or system states.

Whether a *static* or *adaptive* approach should be adopted is, amongst others, a function of the level of uncertainty over the planning horizon, the degree of flexibility of the solutions that form part of particular strategies (i.e. how *easily* changes can be made to solutions) and the time it takes to implement solutions that form part of a certain long-term strategy relative to the rate of change of the system (i.e. how *quickly* the system can adapt if it needs to; how *quickly* actions can be implemented, and how *quickly* the system responds) (Fig. 4).

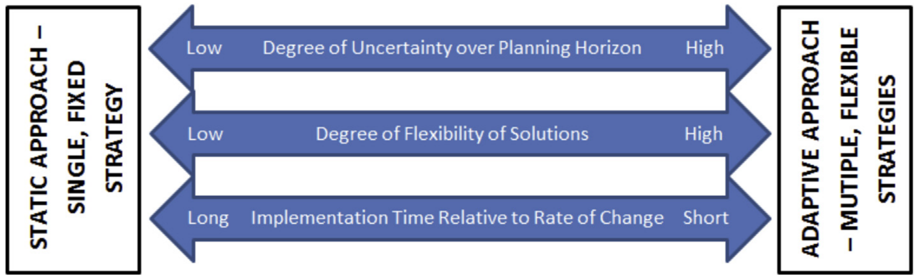

Fig. 4. Conceptual representation of conditions favouring the two main approaches to developing solutions when faced with multiple plausible futures.

Adoption of a static approach featuring a single, fixed strategy that is robust under as many plausible future conditions as possible is not preferable when the level of uncertainty over the planning horizon is high. This is because static strategies that have to cater to a wider range of conditions have to be more conservative, which is likely to incur high economic, social and/or environmental costs. In addition, as it is not possible to conceive of all plausible futures at the beginning of the planning period for highly uncertainty systems, static strategies designed to be robust under a certain set of future conditions might still fail if the future unfolds in a direction that was not considered.

The *flexibility* (or *adaptivity*) of a strategy is expressed by the ability to switch to, or add another solution, or adapt the current solution (Haasnoot, 2013; Rosenhead et al., 1972; Wong and Rosenhead, 2000). Flexible solutions can be adapted (e.g. intensification of an action), abandoned (switch to a different solution), or extended (add a solution). They do not result in lock-ins and have little influence on potential future options (i.e. they have fewer path-dependencies). If solutions that form part of the proposed strategy are inflexible (e.g. altering large infrastructure with a long life time), adaptation is more difficult and consideration of a single, static solution provides a potentially attractive option. In contrast, if the component solutions of a strategy are relatively flexible (e.g. operational decisions), an adaptive strategy is likely to be favoured. However, even if adaptation is relatively easy from a physical or technical perspective, such changes might have significant negative implications from a financial or institutional perspective, or may even have large negative consequences for society. Consequently, these factors also need to be taken into account (Dewulf and Termeer, 2015; Szemis et al., 2014; Van der Brugge and Roosjen, 2015).

If the time it takes to implement a solution is long relative to the rate of change of the system, the implementation of a single, static strategy that performs well under a range of plausible futures is likely to be a better option, as adaptation might not be able to be achieved sufficiently quickly to avoid system failure. In contrast, if the time required for the system to adapt is short relative to the rate of change the adaptation is designed to respond to, an adaptive approach is likely to be an attractive option.

While Fig. 4 and the accompanying discussion highlight the conditions under which static and adaptive approaches are preferred, in practice, there are likely to be many situations where an adaptive approach is preferred for one or two of the three criteria considered, while a static approach is preferred for the other(s). For example, if we consider the case of urban water supply augmentation over a period of 50 years, where the degree of uncertainty is high due to a range of plausible changes in demand and supply as a result of changes in climate and population, an adaptive approach would be preferable in accordance with the criterion represented by the top arrow in Fig. 4. However, the degree of flexibility of the infrastructure solutions that form part of urban water supply expansions is generally low, favouring a static approach. Similarly, the lead times associated with the implementation of large infrastructure projects are generally long, possibly also favouring a static approach, depending on how quickly demand and/or supply are changing due to climate and population drivers relative to the lead time associated with implementation. In such situations, hybrid approaches can be used. For example, the approach of Beh et al. (2015a) is suitable for conditions where the degree of uncertainty over the planning horizon is high, but the degree of flexibility of the solutions is low and the implementation time relative to rate of change is long. This is achieved by allowing adaptation at fixed time intervals over the planning horizon to allow sufficient lead-time for the implementation of adaptation options, while ensuring that the individual strategy that is implemented at each adaptation interval is as flexible as possible, and robust over a wide range of plausible futures during this interval.

6. Implications for modelling

As with any other application of modelling, the treatment of multiple plausible futures is influenced by purpose and context and should be fit for purpose (Black et al., 2014; Jakeman et al., 2006), in this case particularly the needs of policy or planning (Van Delden et al., 2011; Walker, 2000; Walker and Haasnoot, 2011). There are some common model requirements, but there is also significant variation. A first common requirement is that most analyses make use of all three paradigms: use of best available knowledge, quantification of uncertainty, and multiple plausible futures. The modeler needs to be clear about which parts of models are dealt with using which paradigm.

A second common requirement is the need to be open to qualitative input into an otherwise model-driven analysis (Carpenter et al., 2009). As a result of its formalized nature, a model is constrained in the aspects of the future it can explore. This supports systematic approaches, but should not result in an analysis being limited by what an existing model can do. When focusing on best available knowledge, the qualitative input is incorporated by improving the model, but when considering multiple plausible futures, it may make more sense to include the information within the broader analysis context (e.g. Greiner et al., 2014; Rozenberg et al., 2014; Walker, 2000). For example, understanding of real-world decision making can be included within a model in its best available or uncertain form, or can be discussed in a workshop setting at the time the model is used. Furthermore, simulations of multiple plausible futures can be complemented with narratives to provide a richer and more complete picture of the way these futures might unfold (Van Delden and Hagen-Zanker, 2009; Van Delden et al., 2011).

The breadth and depth of a model's scope can vary significantly. For more exploratory methods (Fig. 3) with broad policy scopes (Walker and Haasnoot, 2011), the flexibility required of the models to deal with a range of disciplines and related drivers and driver extents increases (Van Delden and Hagen-Zanker, 2009; Van Delden et al., 2011). Conversely, for less exploratory methods with narrow policy scopes, there tends to be a greater emphasis on historic calibration and validation. Consistency with history is important in BAU and trend scenarios, notably when the aim is to assess implications of one policy alternative against another, or a 'do nothing' alternative (Van Delden and Engelen, 2006). For modelling to be able to support exploratory scenarios, the interactions between processes, and especially their ability to change over time due to various developments, increases in importance, together with the ability to deal with a wide range of drivers, directions and magnitudes. In this context, broader directions become more important than details.

Model requirements can vary even for a given model scope, depending on the approach used. Exploratory contexts often benefit from more qualitative information and a greater level of participation from a wide range of relevant stakeholders or domain experts. Where quantitative techniques are used to computationally explore a broad range of futures, the emphasis is on fast models that satisfy specific policy-relevant accuracy requirements (Haasnoot et al., 2014), and within which uncertain elements within models can be manipulated programmatically. These requirements are not necessarily incompatible, but there may be a broad range of means by which they can be combined. Even in seemingly obvious cases, such as capturing adaptive actions with a model, there is some freedom as to whether the actions are modeled endogenously, manipulated as an input to a model run, or treated qualitatively using multiple scenarios. The difference is not necessarily one of depth, but rather of preferred paradigm. Further guidelines do exist on model characteristics to tackle uncertain futures (e.g. Walker and Haasnoot, 2011), but in the context of understanding the future, a common element is nearly always a sensitivity to the particularities of a context – to understand the 'customer', rather than let the analysis be driven by the available 'technology' (Walker, 2000).

7. Summary and concluding remarks

The need to deal with an uncertain future as a result of changes in climate, technology, socio-economic conditions and politics has led to the realisation that traditional methods of dealing with uncertainty that are based on probability distributions surrounding a "best-guess" of the future are unlikely to be appropriate. This has precipitated the development of a number of concepts that consider multiple plausible futures, such as deep uncertainty, global uncertainty and VUCA, highlighting the independent evolution of thinking about this emerging and important topic in different disciplinary areas.

The characterisation of uncertainty in terms of multiple plausible futures has flow-on effects in terms of:

- The way uncertainty is quantified: Rather than just sampling from probability distributions, different plausible future pathways are represented as scenarios that generally represent coherent storylines that are based on particular assumptions.
- The way system performance is measured: Rather than representing performance in terms of the probability of violating specific values related to a "best-guess" future, it is represented in terms of the robustness (insensitivity) of performance to a range of plausible futures.
- The way strategies or designs are developed: Rather than only considering single, static strategies or designs, the use of multiple, adaptive strategies might provide an attractive alternative, depending on the attributes of the problem under consideration.

While a good understanding of the linkages between the above factors is vitally important when dealing with a highly uncertain future, so is a good understanding of the categorisation of the individual methods that can be used within each category. To this extent, this paper provides perspectives on how:

- Consideration of multiple plausible futures is one of a number of complementary paradigms for considering an uncertain future.
- Deep uncertainty is one of a number of terms used to encapsulate the concept of multiple plausible futures.
- Different types of scenarios have different degrees of suitability for exploring multiple plausible futures.
- Different criteria that determine whether static or adaptive strategies are preferred and how they can be in conflict with one another.

In conclusion, we hope that the articulation of (i) different paradigms for representing an uncertain future, (ii) different terms that can be used to encapsulate multiple plausible futures, (iii) different types of scenarios and the role they play in quantifying an uncertain future, (iv) different approaches to developing robust strategies and the criteria that favour one over the other and (v) different issues to consider when developing models when dealing with multiple plausible futures presented in this paper will be useful for researchers and practitioners as they endeavour to develop robust strategies in the face of a highly uncertain future.

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