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Key Points:
- A generalized method is developed to aid robust water planning using probabilistic information
- The joint probability of plausible futures is estimated using Bayesian belief networks
- Application to the Mwache Dam, Kenya, shows the added value of additional information

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Incorporating Multidimensional Probabilistic Information Into Robustness-Based Water Systems Planning

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Abstract The widespread uncertainty regarding future changes in climate, socioeconomic conditions, and demographics have increased interest in vulnerability-based frameworks for long-term planning of water resources. These frameworks shift the focus from projections of future conditions to the weaknesses of the baseline plans and then to options for reductions in those weaknesses across a wide range of futures. A consistent challenge for vulnerability-based planning is how to assess the relative likelihood of the occurrence of the multidimensional and codependent uncertainties to which the system or plan is vulnerable. This work proposes a methodological solution to the problem, demonstrated in this case as an extension to Decision Scaling framework. The proposed approach first generates a wide range of futures using stochastic simulators, and then stress tests the system across those futures to identify vulnerabilities relative to stakeholder-defined performance thresholds. The relative likelihood of the vulnerabilities is then explored using a Bayesian belief network of the knowledge domain of the water resources system. The Bayesian network provides a formal representation of the joint probabilistic behavior of the system conditioned on the uncertain but potentially useful sources of information about the future, including historical trends, expert judgments, and model-based projections. The proposed approach is applied to compare four design options for a dam project in the Coastal Province of Kenya with respect to the reliability and net present value metrics. Results show that incorporation of belief information helps better distinguishing of the available options, principally by magnifying the differences between the computed net present values.

1. Introduction

Planners of water resources infrastructure and other similarly long-lived development projects face major challenges in coping with uncertainty from environmental, demographic, and financial factors, among others. Increasing hydrological evidence shows that anthropogenic climate change is altering the spatial and temporal variability of water resources by affecting precipitation quantities and patterns, evapotranspiration rates, and the frequency and intensity of storms (Arnell & Gosling, 2013; Stocker et al., 2013). Accelerated rates of change in population growth, urbanization, water use efficiency, and consumption patterns simultaneously result in unpredictable shifts in long-term water and energy demands (Alcamo et al., 2007; Arnell & Lloyd-Hughes, 2014; Vorosmarty et al., 2014). In many parts of the world, and in particular where new water infrastructure is most needed, political instability, market fluctuations, and rapidly changing societal preferences make it difficult to weight present and future costs and benefits of long-lived development projects, such as large-scale dams (Heal & Millner, 2014; Jeuland, 2010). Moreover, for many projects, estimation of the uncertainty bounds faced by the planners is complicated by the interdependencies between the multiple uncertain factors; for example, land-use and climate conditions (Collins et al., 2002; Pahl-Wostl, 2007).

The occurrence (and amplification) of complex, nonstationary stressors in long-term water resources planning has motivated an interest in approaches for "decision-making under deep uncertainty" (Dittrich et al., 2016; Hall et al., 2012; Haasnoot et al., 2013; Kwakkel et al., 2016; Maier et al., 2016; Walker et al., 2013). These approaches avoid reliance on predictive assumptions about the future and instead take the future to be unknowable, with information about the true range of possible futures, including any associated probability distributions, understood to be incomplete, inconsistent, or nonexistent (Lempert et al., 2004). Under a deeply uncertain future, it is no longer possible to plan based on historical data, such as the statistical analyses of weather conditions or extremes (Brown, 2010; Milly et al., 2008; Stakhiv, 2011). In the deep uncertainty paradigm, scenarios developed from the projections of future climate change, forecasts of water demand, economic development, demographic movement, or similar, are reduced in usefulness by the potentially overwhelming range of uncertainty they span (Dessai & Hulme, 2009). This is because such information is imprecise in nature due to a number of epistemic (knowledge-related) and ontological factors, including an incomplete understanding of the underlying systems and feedback mechanisms, subjective assumptions on unknowable future human behavior, and the intrinsic variability (randomness) in nature (Dessai & Hulme, 2009; Haasnoot et al., 2012; Thompson et al., 2015; Walker et al., 2003; Wilby, 2010).

One common approach to cope with deep uncertainty is to attempt to reduce vulnerabilities across many plausible futures (Brown & Wilby, 2012; Maier et al., 2016; Weaver et al., 2013; Wilby & Dessai, 2010). This typically involves a description of potential system vulnerabilities in terms of a preferred performance measure (e.g., based on an unacceptable level of reliability or costs), followed by procedures for identification of robust solutions (i.e., those that perform acceptably well across a wide domain of future conditions; Giuliani & Castelletti, 2016; McPhail et al., 2018). When quantifying robustness, "acceptable performance" can be defined in multiple ways: for example, based on a critical performance threshold such as a minimum flow requirement (Kasprzyk et al., 2013; Singh et al., 2015), regret due to deviation from some baseline or expected performance (Spence & Brown, 2016; Taner et al., 2017), or magnitude of variation in performance across multiple futures or scenarios (Giuliani & Castelletti, 2016; Kwakkel et al., 2015). Independent of the measure, robustness-based planning requires a systematic, unbiased, and fuller sampling of conditions that may occur over the planning period, without being constrained by a narrow range of prescriptive storylines or scenarios. Typically, no prior judgment is made on the occurrence likelihoods of possible future states, rather than an implicit inference to define a feasible range for the uncertainty domain. For example, Robust Decision Making uses "scenario discovery," a form of cluster analysis to find conditions where the system would be under most stress in the future, without assigning any weights to individual scenarios (Bryant & Lempert, 2010). Info-Gap theory conceptualizes robustness as the greatest level of the radial distance around a starting point (e.g., a best-guess estimate of the future) with satisfactory performance across a prespecified uncertainty space (Ben-Haim, 2006; Sniedovich, 2010).

This work is informed by a long-standing debate regarding the value and use of probabilistic information to support robustness-based planning (Borgomeo et al., 2018; Groves & Lempert, 2007; Parson et al., 2007; Shortridge et al., 2017). One side of the debate suggests that there is no value in using probabilities, as such information may imply a greater degree of certainty about the future than exists and that the inference may, in turn, be misleading for decision-makers (Dessai & Hulme, 2004; Gong et al., 2017; Groves & Lempert, 2007; Lempert, 2000). When probabilistic information is not considered, each potential vulnerability is equally important on the overall robustness, which can also be interpreted as an implicitly equal weighting. On the other hand, some studies combine robustness-based approaches with probability weights derived from climate projection ensembles, paleodata, expert elicitations, or similar (Borgomeo et al., 2014; Borgomeo, Naenini-Mortazavi, et al., 2015; Manning et al., 2009; Moody & Brown, 2012; Shortridge et al., 2017; Shortridge & Zaitchik, 2018). These studies provide an additional layer of information that may be potentially useful for making more informed decisions, without obscuring the results of the vulnerability analyses. For example, by integrating probabilistic information into vulnerability analyses, one can explore the sensitivity of robust decisions to multiple probability distributions (Moody & Brown, 2013; Whateley et al., 2014), or compare trade-offs between plan costs and robustness under different levels of risk (Borgomeo et al., 2014, 2018).

Decision Scaling framework (Brown et al., 2012) provides an example of how one can combine the results of a climate vulnerability analysis with probabilistic or quasi-probabilistic information from climate projections, or other sources of climate information. Decision scaling first uses stochastic weather generators to develop a wide range of possible future local conditions and then "stress tests" the system across those conditions to identify problematic futures that lead to unacceptable outcomes. After vulnerabilities are identified, different sources of information, for example, projections, historical trends, expert opinion, are examined for determining the probability of problematic future conditions. For example, in Brown et al. (2012), the count of climate model projections was used as an indication of probability, with the assumption of equal weight for each model. This was followed by the use of fitted multivariate probability distributions in Moody and Brown (2013) and Whateley et al. (2014). Having decided that the assumption of equal likelihood and independence of projections is not supported, more sophisticated probability estimation techniques were presented in Steinschneider et al. (2015). These past efforts to inform vulnerability analyses with probabilistic beliefs have only focused on climate information from paleodata, global or regional climate projections, or expert judgments.

This paper represents the next advance, where we now look beyond climate uncertainty and introduce a formal, generalized framework to make full use of probabilistic knowledge or beliefs about multiple environmental, demographic, and financial uncertainties in long-term water planning. The coupling of multiple sources and types of belief information with vulnerability analysis for informing water planning decisions presents several challenges. First, subjective beliefs about relevant environmental, demographic, and financial factors cannot be evaluated in isolation due to the codependencies among the uncertainties they describe (Döll et al., 2014; Pahl-Wostl, 2007; Sperotto et al., 2017). Examples of such dependencies include climate and price elasticity of household water demand (Franczyk & Chang, 2009; Schleich & Hillenbrand, 2009), climate variability effects on regional development (Brown et al., 2011; Hurd et al., 2004; Olmstead, 2014), and climate change effects on land-use patterns (Syvitski, 2003; Vörösmarty et al., 2003). Omitting such codependencies may lead to an underestimation of risks and in turn may result in maladaptive planning. To account for these codependencies requires conditional probability distributions. However, developing conditional probability distributions to represent beliefs about future uncertainties is not a straightforward task as the beliefs used to derive those probability distributions come from diverse knowledge domains (e.g., hydrology, economics, public policy) and are in disparate forms (e.g., model-driven time-series data, point-estimate projections, qualitative survey results, or expert judgments).

To address these challenges, we propose "Bayesian Networks Decision Scaling" (BNDS). In the proposed approach, we first conduct a multidimensional stress test of the water resources system or investment plans across the prespecified set of environmental, demographic, and financial uncertainties through exploratory modeling (e.g., Ray et al., 2018). At this phase, our goal is to have the best estimate of the true range of vulnerabilities that may occur over the planning horizon, without being constrained by scenarios or probability distributions derived from model projections or expert judgments. After identifying a fuller picture of the vulnerabilities, we then seek answers to the question of "what are the relative likelihoods of conditions associated with vulnerable futures?" We attempt to answer this question through a Bayesian belief network (BBN), which is used to estimate a posterior joint probability distribution of the future states explored previously. In this process, a BBN addresses the challenges arising from multidimensional uncertainties by providing a formal way to account for the conditional dependencies among multiple factors and providing a technique to blend the best available information from multiple, divergent information sources. Finally, we combine the results from the vulnerability assessment and the probabilistic inference from the BBN for a belief-informed robustness analysis, which can be used for a direct comparison of planning alternatives.

BNDS provides the tools for estimation of the likelihood of multidimensional futures consisting of nonindependent uncertainties, essential for multidimensional risk assessment (and, subsequently, risk management), but previously lacking. It does this while drawing a clear distinction between the processes of vulnerability exploration and probabilistic inference based on subjective beliefs about the future. In doing this, it deemphasizes conflicts in beliefs by focusing the discussion on clearly defined system vulnerabilities and motivating adaptation actions subject to a post-process sensitivity analysis of beliefs regarding future conditions. This is in contrast to the use of belief information in top-down or predict-then-act approaches, where such information is used directly to obtain a set of prescriptive scenarios, which commonly results in spanning a narrow and potentially biased fraction of possible futures (Lempert, 2003; Weaver et al., 2013) and a cascading pyramid of uncertainty from one modeling step to another (Giorgi, 2005; Wilby & Dessai, 2010).

The remainder of this paper is structured as follows. In section 2, we introduce the BBN concepts and its past uses in water resources planning. In section 3, we introduce the procedures of the BNDS framework for water planning under uncertainty. In section 4, we illustrate the proposed framework over a water supply design study in Mombasa, Kenya. Section 5 contains the results and the discussion of the case study application. Section 6 presents the conclusions from the study.

2. BBNs

BBNs are statistical models that are used for knowledge representation and reasoning across many fields from environmental science to medical research (Aguilera et al., 2011; Newton, 2010; Pearl, 1988). BBNs allow representation of uncertainty through a graphical network of variables, where the degree of belief on each variable is represented by a conditional probability distribution and the strength of the relationships between the connecting nodes is specified by node probability tables (NPTs). A fundamental feature of BBNs is the "conditional independence" or the absence of a connecting arrow between any two nodes. This feature allows NPTs to be generated "locally" by only considering the immediate parent nodes of the node being quantified, so all other entities are statistically independent, conditional upon the network structure. The joint probability density function (PDF) of a BBN with n discrete random variables $\{X_1, \dots, X_N\}$ is propagated using the chain rule (Jensen & Nielsen, 2007):

$$P(X_1, \dots, X_N) = \prod_i^n P(X_i| \, pa(X_i)), \tag{1}$$

where $pa(X_i)$ is the probability distributions for the parent nodes of X_i, $P(x_i| \, pa(X_i)$ is the conditional probability distribution of X_i given its parent values. Once the network structure is generated, belief updating can be performed using Bayes rule (Pearl, 1988):

$$P(X_i|e) \propto P(e|X_i)P(X_i), \tag{2}$$

where $P(X_i)$ is the prior probability, $P(e| \, X_i)$ is the likelihood function based on information e, and $P(X_i| \, e)$ is the posterior probability distribution (the probability of X_i after information e). In equation (2), e may be in the form of hard evidence specifying a definite finding, or soft evidence specifying a new probability distribution for the variable. In the former case, belief updating takes place by instantiation of the variable X_i to its finding, that is, entering the probability weight $P(X_i = x_i) = 1$; whereas in the latter case, the posterior probability distribution can be directly replaced by the new probability distribution. In the context of long-term water planning, belief updating with soft evidence is more relevant, as information about the future conditions such as demand levels never indicates a certainty, but rather (optimistically) a refined belief about how the future may unfold.

There are several well-established advantages of BBNs for making probabilistic inference over a knowledge domain. First, BBNs are flexible regarding data requirements and processing, allowing them to combine knowledge of different source and accuracy in highly complex and multidisciplinary problems (Getoor et al., 2004). Second, BBNs can provide a transparent, participatory modeling interface, where information from multiple stakeholders or experts can be incorporated in the form of subjective beliefs or elicitations, and easily revised when needed (Kjaerulff & Anders, 2013; Kumar et al., 2008; Newton, 2010). Third, BBNs can handle situations where underlying data are missing or sparse, through learning algorithms that iteratively provide maximum likelihood estimates for the parameters given the data and model structure (Uusitalo, 2007). Finally, BBNs can be easily incorporated into traditional decision analysis frameworks such as cost–benefit analysis (Åström et al., 2014; Lee et al., 2009), or used within dynamic contexts for making probabilistic inference over multiple time stages (Yet et al., 2016).

There is a growing body of literature in the use of BBNs to support water resources decision-making (for detailed reviews, see Castelletti & Soncini-Sessa, 2007; Aguilera et al., 2011; Sperotto et al., 2017). Kuikka and Varis (1997) show one of the first applications of this kind by using expert knowledge to assess climate change effects on watershed-level planning. Recently, BBNs have been used to support decision-making in urban infrastructure planning (Noi & Nitivattananon, 2015), irrigation system designs (Batchelor & Cain, 1999; Henriksen & Barlebo, 2008), environmental flow allocations (Chan et al., 2012; Pollino et al., 2007; Stewart-Koster et al., 2010) and sea level rise adaptation (Catenacci et al., 2013), and flood risk reduction (Noi & Nitivattananon, 2015). Some studies discuss the integration of BBNs with other decision-analysis tools and modeling techniques in water planning or similar fields. Castelletti and Soncini-Sessa (2007) state that BBNs can be used to model an entire water resources system, or a specific component (e.g., hydrology, reservoir operations, water quality). They conclude that BBNs can be particularly useful when there is no theory to support quantitative model formulations, in contrast to mechanistic models that quantify well-established theories about internal system processes. In this context, BBNs have been integrated with rainfall-runoff (Dyer et al., 2014), groundwater (Martínez-Santos et al., 2010; Molina, 2013), and water quality models (Mesbah et al., 2009). Aside from the coupling of BBNs with mechanistic (process-based) models, several studies demonstrate the use of BBNs within decision support systems. Bertone et al. (2015) developed a risk assessment tool for managing the effects of extreme weather events, in which they use a Bayesian network to estimate the likelihood of meeting water quality targets and a system dynamics model to assess the effectiveness of policy responses. Kocabas and Dragicevic (2013) used a Bayesian network to obtain decision rules related to land-use management choices of individuals, which are then used in an agent-based modeling framework to simulate land-use dynamics.

3. BNDS

The proposed framework (Figure 1) begins with a bottom-up project screening process to describe the water resources planning problem, consisting of planning alternatives, exogenous uncertainties, performance metrics, and vulnerability thresholds. Vulnerability analysis is then applied to reveal the conditions associated with poor performance outcomes and identify the most important exogenous factors. In the next phase, a BBN is used to make a probabilistic inference on whether the previously identified vulnerabilities are likely to occur based on best available belief information. Finally, the results from the vulnerability analysis and probabilistic inference are evaluated together through multidimensional visualization techniques and summarized through a belief-informed robustness metric. These four major phases are discussed below; while the framework is demonstrated in a case study in Section 4.

3.1. Phase 1: Project Screening

The first phase of the framework defines essential components of the water system analysis such as the key uncertainties for the evaluation, performance measures, and vulnerability thresholds with the inputs from project stakeholders, for example, associated local organizations, project partners, funding agencies (Pahl-Wostl, 2002; Ray & Brown, 2015). Uncertainties typically include natural (hydroclimate) variability in the water resources system and a set of exogenous factors $\{X_1, X_2, \ldots X_m\}$ to represent major environmental, demographic, and financial factors relevant over the planning horizon of the project (e.g., 50 years). Exogenous uncertainties are long-term changes in hydroclimate variables such as temperature, precipitation, streamflow or evapotranspiration, demographic variables such as population growth rate or income level, and other project-specific variables such as economic lifetime, construction delays, capital and maintenance costs, the economic value of the services provided by the infrastructure, or similar. Performance measures quantify performance under the evaluated futures based on the objectives of the study, which may include water system measures of reliability or resilience as well as financial measures such as Internal Rate of Return or Net Present Value (NPV; Loucks et al., 2005). Finally, vulnerability thresholds define the acceptable limit of each performance metric based on the planning objectives or stakeholder preferences, for example, a water reliability target of 95%. Specifying vulnerability thresholds may be challenging, when there is no empirical data about critical tipping points (such as a minimum discharge requirement for protecting downstream ecology) or when there is a lack of consensus among the experts. In such cases, analysts can define vulnerability thresholds based on the spread of historical or model-simulated performance, for example, based on the outcome at the 90th or 95th percentile value of an output variable (Kalra et al., 2015; Kasprzyk et al., 2013).

3.2. Phase 2: Vulnerability Analysis

The second phase of the analysis aims to provide a good understanding of the most important factors and the set of specific conditions or states of the worlds (SOWs) that may lead to vulnerable outcomes in terms of the predefined performance measures and vulnerability thresholds. The process begins with generating or sampling a sufficiently wide range of plausible futures to best describe the true range of uncertainty. Here, we assume that each feasible SOW is obtained by the combination of two components: stochastic realizations of natural variability and a random sample of exogenous factors that are generated from the uncertainty ranges of each factor. Natural variability is commonly represented as synthetic climate time-series data obtained from a stochastic weather generator (Steinschneider & Brown, 2013). However, in some cases, it can be desirable to sample natural variability in hydrological conditions directly using a synthetic streamflow generator (Borgomeo, Farmer, & Hall, 2015; Henley, 2012; Herman et al., 2010), particularly when hydrologic models are not available and/or the development of such models is costly. A random sample of

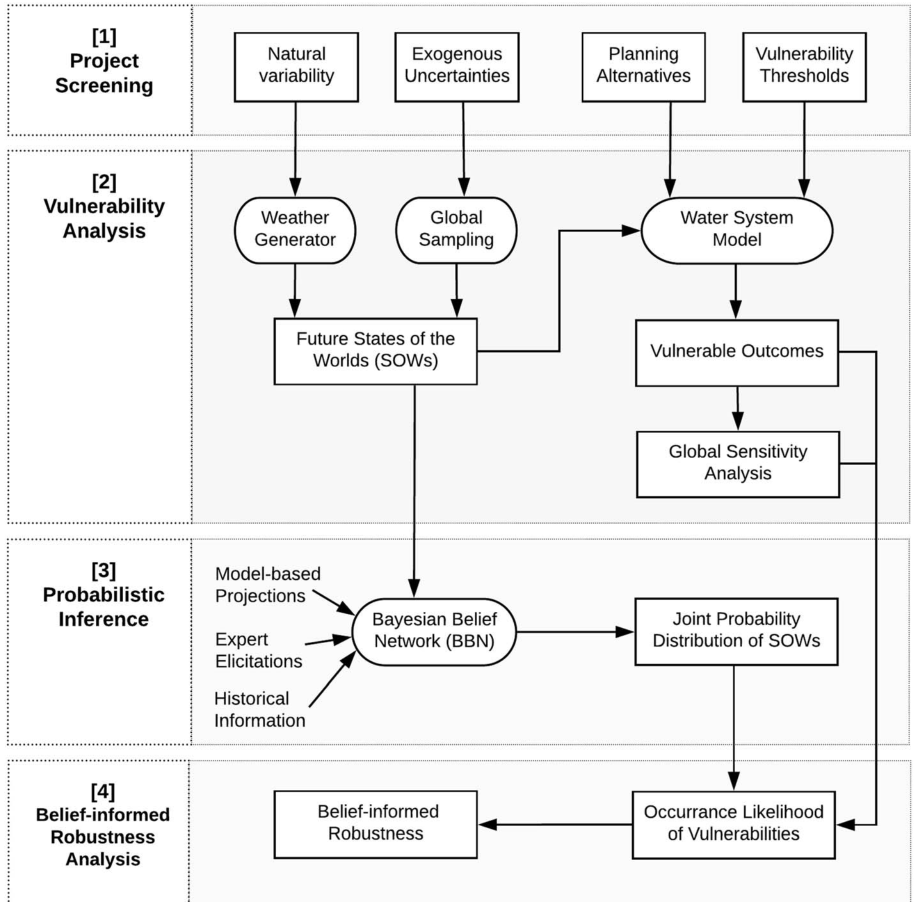

Figure 1. Conceptual flow chart of the proposed method.

exogenous factors, $x_1, \ldots ,x_m$, can be generated by Latin Hypercube Sampling (LHS; McKay et al., 1979). LHS samples are be obtained by dividing the continuous uncertainty range of each factor into n equal intervals and generating an $n \ x \ m$ matrix, where each factor interval is sampled exactly once. The domain of SOWs $\theta \in \boldsymbol{\Omega}$ is then defined by combining n stochastic climate variability realizations and the $n \ x \ m$ LHS matrix, where each sampled factor interval is expressed by its midpoint value.

Next, system vulnerabilities are explored across the range of SOWs sampled using a chain of relevant system models to simulate hydrology, reservoir operations, water quality, and hydroeconomic models or similar. The modeling step relates the future conditions to long-term performance $y = f(\theta, d)$, where d represents specific design configurations or operational rules associated with the problem. The computed vector of performances $\boldsymbol{Y_d} = \{\mathrm{y}_1, \ \ldots \ , \mathrm{y}_\mathrm{n}\}$ is then parsed into a binary variable to distinguish acceptable (satisfactory) and unacceptable (failure) performance outcomes with respect to the specified vulnerability thresholds (see Bryant & Lempert, 2010; Whateley et al., 2014). This process, also referred to as a multidimensional stress test can be used to assess the planning alternatives and identify the options that yield the largest range of acceptable performances (Ray et al., 2018). Note that at this stage, no subjective inference is made on the likelihood of the vulnerabilities.

A sensitivity analysis can be conducted locally by perturbing the uncertain factors and assessing the impacts on the simulation results, or globally by considering the variations within the entire space of variability of the input factors simultaneously (Paton et al., 2013; Saltelli et al., 2000). The latter can be done by a variance-based method such as Sobol analysis, an Extended Fourier amplitude sensitivity test, or a sampling-based method such as partial rank correlation coefficient (Marino et al., 2008). The choice of a method depends on the types of models used in the analysis and the type of the relationships between the input and output variables (e.g., linear or monotonic), and it is advisable to use more than one method, if possible (Gao & Bryan, 2015; Kasprzyk et al., 2013; Vano et al. 2015). In addition, the relative importance of the uncertain factors on unacceptable or vulnerable outcomes can be identified using a regional sensitivity analysis, sometimes called Monte Carlo filtering (Pianosi et al., 2016). In this work, we carry out a regional sensitivity analysis to isolate the uncertain factors most responsible for vulnerabilities and ignore the remaining.

3.3. Phase 3: Probabilistic Inference

The previous phase focused on exhaustive identification of vulnerabilities over a wide range of futures, without regard to the occurrence likelihood of those possible conditions. In practical cases, there is a need to prioritize among vulnerabilities when considering a range of planning options for adaptation. Uncertain but informative projections or predictions can be useful for such a prioritization of vulnerabilities for decision-support. In Phase 3, belief information is processed through a formal probabilistic approach for making an inference on the likelihoods of the vulnerabilities. The process of probabilistic inference involves two steps. First, a BBN model is defined to describe the influence relationships among the exogenous factors considered in the problem in probabilistic terms. Next, this BBN is used to obtain the joint occurrence probability of each SOW explored in Phase 2 by incorporating belief information.

The structure of the Bayesian network represents the direction of the causal or correlational relationships among the exogenous factors considered in the problem representing environmental, social, and financial uncertainties. These relationships can be specified with the project stakeholders based on a shared understanding of the system and its components, or simply based on empirical knowledge (see Chan et al., 2010; Maskrey et al., 2016). Each factor in the network is represented by n discrete states consistent with the sampling scheme used in Phase 2. This consistency ensures that a joint probability weight can be computed for any given future state i $P(\boldsymbol{\theta_i}) = P(x_{1,i},..,x_{m,i})$, $\boldsymbol{\theta_i} \in \boldsymbol{\Omega}$. In the process of model development, one major burden is to generate NPTs that describe the potentially complex and nonlinear set of relationships among the nodes in probabilistic terms (e.g., between different states of temperature and water demand). In the common practice, such information can be obtained from stakeholder workshops (Batchelor & Cain, 1999) or one-on-one interviews with the experts (Borsuk et al., 2001; Richards et al., 2013). For complex model structures with a large state space, empirical data or expertise can be directly encoded into NPTs by learning algorithms such as NoisyOR (Fenton et al., 2006) or Expectation Maximization (Uusitalo, 2007). In this work, we address the problem of NPT generation by a relatively simple procedure. First, we describe each conditional variable through a truncated normal distribution $\psi(\overline{\mu}, \ \sigma^{-}, a, b; X)$, where $\overline{\mu}$ and σ^{-} are the mean and variance of the distribution and a and b specify the truncation interval. The parameters $\overline{\mu}$ and σ^{-} are specified through transfer functions based on the values of the parent nodes, for example, $\overline{\mu} = f(pa(X_i))$ and $\overline{\sigma} = g(pa(X_i))$, and a and b correspond to the prespecified lower and upper limits. These truncated normal distributions are then used to obtain the normalized probability weights of each possible variable state corresponding to n discrete intervals. The parameter values are set based on expert options, historical data, or model outcomes.

In the last step of Phase 3, the BBN is used to propagate the joint probability weight of each SOW $P(\boldsymbol{\theta_i}|e),\boldsymbol{\theta_i} \in \boldsymbol{\Omega}$ by the chain rule (equation (1)). Note that the BBN used in this step does not aim to sample future states or vulnerabilities, which was done in Phase 2 (Figure 1). Here, the BBN is only used for approximating the relative plausibility of the range of predefined SOWs to provide additional information for decision-making. By doing this, the procedures for vulnerability analysis and probabilistic inference is clearly separated to reduce the risk of overlooking vulnerabilities that were believed, a priori, to be unlikely. This use of a BBN is different from the common use, where they are used to sample uncertain factors and describe how the system could respond to the sampled states.

3.4. Phase 4: Belief-Informed Robustness Evaluation

The final phase combines the results from the previous two phases by visualizing the vulnerabilities across the multivariate uncertainty space and by assessing the options in terms of robustness. While the common motivation in robustness analyses is identifying alternatives that are relatively independent of future (Herman et al., 2015; Matalas & Fiering, 1977), the particular choice of metrics used to quantify robustness depends on the decision maker's attitude about the future. For example, under the case of extreme pessimism, the *maximin* metric allows making decisions by the worst-case scenario; whereas on the other hand, *maximax* metric focuses on the best possible scenario (Giuliani & Castelletti, 2016). In water planning, two commonly applied robustness measures are satisficing and regret metrics (McPhail et al., 2018). The former case of satisficing-based robustness is defined as the ability to meet a specified vulnerability threshold and hence provide adequate performance, whereas regret-based metrics, on the other hand, focus on minimizing the opportunity cost of choosing incorrectly (for a detailed discussion see McPhail et al., 2018; Giuliani & Castelletti, 2016).

What is common across both satisficing and regret-based metrics of robustness is an (implicit) assumption that each possible future state is equally important in the robustness calculations, including the states that are extreme or potentially unlikely to occur. In the context of climate change, Moody and Brown (2013) presented an alternative way to weight the plausible states when calculating robustness. This approach, termed as "climate-informed robustness" allows placing a higher weight to climate changes that are consistent with historical trends and climate change projections than those that are consistent with only one or none of these information sources (Whateley et al., 2014).

In this work, we propose "belief-informed" robustness as a more generalized form of climate-informed robustness index:

$$RI = \sum_i \Lambda(\boldsymbol{\theta_i}, d) P(\boldsymbol{\theta_i}|e), \tag{3}$$

where $\Lambda(\boldsymbol{\theta_i}, d)$ is the binary performance function representing system vulnerabilities and $P(\boldsymbol{\theta_i}|e)$ is normalized weight assigned to the future state θ_i. In equation (3), $P(\boldsymbol{\theta_i}|e)$ is directly obtained from the probabilistic inference using BBN (Phase 2), which blends available sources of probabilistic information on future environmental, social, and financial conditions.

4. Application to the Mwache Dam, Kenya, Shows the Added Value of Probabilistic Information

4.1. Project Screening for the Proposed Water Supply

The planned location of the Mwache Dam is on the Mwache River, about 22 km southwest of Mombasa (Figure 2). Estimated water deficits in the greater Mombasa region are as much as 60% of the total demand of 130 MCM (million cubic meters) per year, with both the total demand and deficit expected to increase with demographic and socioeconomic growth (Tahal, 2013). Upon completion, the Mwache Dam is expected to provide an additional supply of about 80 MCM per year to Mombasa, of which 80% is expected to be used for augmenting Mombasa's domestic supply. The remaining 20% supply will be used to support irrigated agriculture in Kwale County and maintain ecosystem health downstream of the reservoir. However, the long-term performance of the water supply system can be reduced substantially due to reservoir sedimentation. According to the preliminary studies, expected sediment to be deposited in the reservoir over 50 years is up to 30 MCM, corresponding to about 20% to 40% of the total reservoir storage (CES, 2014).

This analysis focused on the evaluation of four engineering design alternatives with gross storage volumes of 80, 100, 120, and 140 MCM and estimated present value costs of US$ 75, 89, 100, and 109 million, respectively (Cervigni et al., 2015). Before the analysis, a project inception workshop was performed in August 2015 bringing together engineering project managers, academics, investors, and a diverse group of Kenyan stakeholders from the Water Resources Management Authority, Coastal Water Services Board, Coastal County representatives, and local universities. The major features of the analysis including the planning objectives, performance metrics, and key uncertainties have been defined from the outcomes of this inception workshop as well as the preliminary project design report (CES, 2014) and the water supply master plan of the coastal province (Tahal, 2013).

The plan is to allocate Mwache water to Mombasa's Mvita, Kauni, and Changwamwe districts, with a demand level of about 38 MCM per year in 2015, which is expected to increase to 65–105 MCM by the year 2035, depending on the level of regional socioeconomic development (CES, 2014). Allocations to agricultural irrigation and environmental flow are as of now expected to be secondary to domestic allocations, though disagreements persist among stakeholders on allocation priorities. Although the region has faced prolonged droughts in the past, this was not raised as a major concern for the stakeholders. For this work, the four design alternatives were evaluated with respect to water service and financial performance. For the

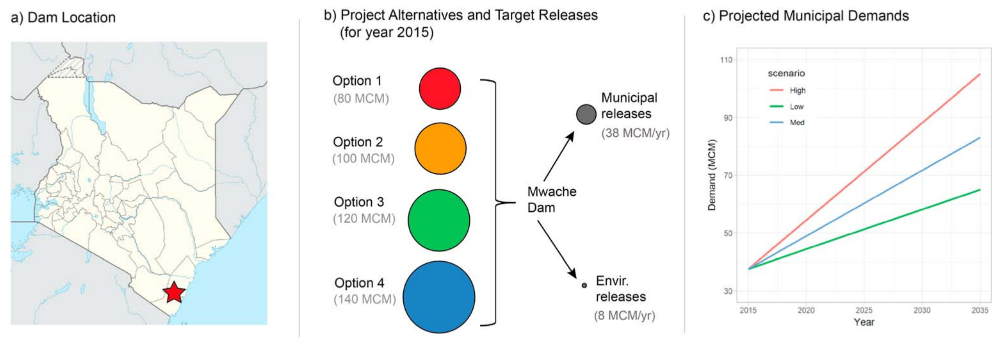

Figure 2. Overview of the Mwache Project. (a) Approximate location of the proposed Dam, (b) storage capacities of four project design alternatives in comparison to annual release targets, proportional to their sizes, (c) Projected Municipal Demands for the Mombasa City.

former, a reliability metric was defined based on the percentage of times that the target water demand can be met (Hashimoto et al., 1982). The financial performance of the system was quantified based on the NPV of the project. The proposed water supply was evaluated across the natural variability of the local climate plus seven exogenous factors: gradual changes in mean annual temperature (°C) and precipitation (%) due to future climate shifts; the specific sediment yield, describing the amount of sediment deposited in the reservoir normalized by the contributing upstream area ($m^3 \cdot km^{-2} \cdot year^{-1}$); annual municipal water demand (MCM per year); price charged for municipal water use (US$ per m^3); and the annual discount rate (%), respectively (Table 1).

4.2. Vulnerability Analysis of the Water Supply System

The analysis begins with generating 1,000 SOWs depicting a wide range of plausible futures. First, an ensemble of one thousand 50-year sequences of monthly climate realizations is generated using a first-order wavelet autoregressive model (Steinschneider & Brown, 2013) to sample the stochastic uncertainty in climate. The climate realizations provided new sequences of monthly minimum, mean, and maximum temperature and mean precipitation while preserving the historical climate statistics (mean, variance, low-frequency precipitation variability) of the observed reference period from the year 1950 to 1999. Next, exogenous factors were sampled from their uncertainty range using LHS and subsequently reordered by the Huntington and Lyrintzist (1998) algorithm to eliminate any potential correlations among the sampled factors. After sampling, each climate realization is incrementally shifted to reflect possible mean climate changes (MCCs), resulting in a total of 1,000 transient climate trajectories. For precipitation changes, multiplicative factors are applied starting from 0% change from historical precipitation, and linearly increasing (or decreasing) to the specified value in the final period (e.g., 120% historical precipitation). For temperature changes, additive factors are applied starting from 0 °C and linearly increasing to the specified temperature increase value in the final period (e.g., 3 °C). Overall, the procedure applied here treats stochastic climate uncertainty (represented by natural variability realizations) as a categorical variable and combines it with the LHS samples representing the deeply uncertain factors. Although not applied in this work, one can also evaluate a

Table 1
The Uncertainties Considered in the Water Supply Design Study

Uncertain factor	Description and uncertainty range
Natural climate variability (NVAR)	Stochastic realizations of the 1950–1999 period
Change in temperature (ΔTEMP)	From 0 to 5 °C increase over the historical mean of 27 °C
Change in precipitation (ΔPRECIP)	From −50% to 50% over the historical mean of 845 mm
Municipal water demand (DEM)	From 60 to 100 MCM per year
Specific sediment yield (SSY)	From 150 to 600 $m^3 \cdot km^{-2} \cdot year^{-1}$
Price charged for water use (PRICE)	From 0.6 to 2.0 USD per m^3
Economic discount rate (EDR)	From 2% to 10%

smaller set of natural climate realizations across each sampled row of deeply uncertain factors to better isolate the adverse impacts of deeply uncertain factors.

The multidimensional stress test was conducted using a parsimonious water system model consisting of a hydrological simulation component to translate monthly precipitation and temperature to streamflow and a reservoir component to estimate monthly water service deliveries to Mombasa. The hydrology component is a conceptual, lumped parameter “abcd” model adapted from Thomas (1981). The model was calibrated for 10 years (1980 to 1990) to fit the monthly historical flows at the River Gauge Station 3MA03, which is located on the Mwache River a few kilometers upstream of the dam site. The calibrated hydrology model yielded a Nash-Sutcliffe efficiency value of 0.64 on the annual time-step, which was deemed adequate considering the limited availability of observed streamflow data. The latter component simulates monthly reservoir operations to provide municipal water to the target districts of Mombasa and environmental discharges to meet the discharge requirements of up to 1.7 MCM per month. Since no further information was available about reservoir operations at the time of the analysis, we assumed a standard operating policy in which demand is satisfied if there is sufficient water in the reservoir, otherwise the reservoir empties (Taner, 2017). The reservoir component also considers the gradual reductions in storage capacity due to sediment deposition. Annual sediment deposition to the reservoir is computed from the specific sediment yield and the reservoir trapping efficiency, which is estimated by the empirical formula given by Brune (1953).

Next, the outputs of the multidimensional stress test were used to calculate the reliability and NPV metrics for each simulation run. Reliability is calculated as the number of months that the reservoir can meet the specified target demand divided by the total number of months in the simulation period. The latter metric of NPV is defined as the total present value of benefits from monthly water service deliveries minus the present value total cost of the project:

$$NPV_{d,i} = \sum_{t=1}^{50} \frac{D(d,i)^{*}PRICE_i}{(1+EDR_i)^t} - C_d, \tag{4}$$

where the planning period begins in the current year $t = 0$ and extends to $t = 50$. Indices d and i indicate the engineering design choice and the future state; C_d is the total cost of the project from the summation of the present value capital cost and the operating and maintenance costs over the life time of the project, $D(d, \theta_i)$ is the total water delivery to the Mombasa city at t in MCM per year; $PRICE_i$ is the unit price charged for municipal water use in US$ per cubic meter, EDR_i is the economic discount rate expressed in decimal form.

The financial performances of different design alternatives were compared in regret terms. NPV regret is calculated from the difference between the best possible NPV value under a given future state $NPV_{d^*,i}$ and the actual NPV obtained in that state $NPV_{d,i}$:

$$NPV\ regret_{d,i} = NPV_{d^*,i} - NPV_{d,i}, \tag{5}$$

The computed reliability and NPV-regret values across each simulation run were then converted to stakeholder-defined vulnerabilities. For reliability, a value of less than 95% is defined as a vulnerability, whereas for NPV-regret, any value greater than US$ 10 million is considered to be a vulnerable result.

In the final step of the vulnerability analysis, a regional sensitivity analysis was applied on the binary performance outcomes for identifying the most important exogenous factors on each performance metric. The sensitivity analysis was carried out using the partial rank correlation coefficient method to take into account nonlinear and monotonic interactions between the model response and the uncertain input factors. The exogenous factors were then ranked based on their influence on the given performance metrics.

4.3. Probabilistic Inference Through the BBN Model

For assessing the likelihood of the future outcomes explored, a Bayesian network was developed (Figure 3). The BBN of the Mwache water supply system consisted of seven random variables that are (1) natural climate variability (NVAR); (2) MCC; 3) future population level of the Mwache supply system (POP); (4) future economic development level (DEV); (5) price charged for municipal water use (PRICE); (6) economic discount rate used in NPV estimation (EDR); (7) specific sediment yield (SSY); (8) and per capita demand for municipal water use (PCD). The nodes NVAR, PRICE, EDR, SSY, PCD, and DEM are discretized into

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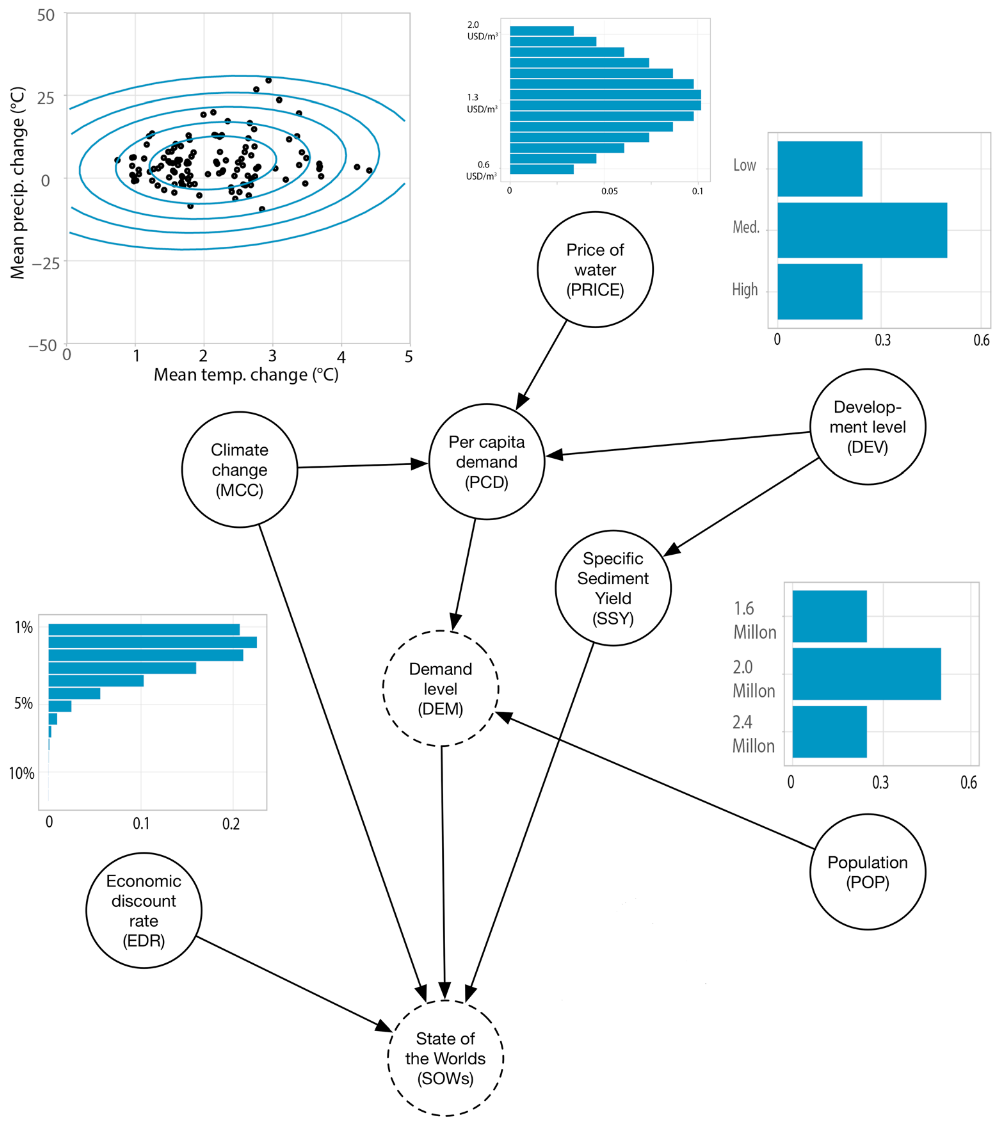

Figure 3. The BBN model Circles in solid and dashed lines show random and deterministic nodes, respectively. The probability weights used for the MCC, EDR, PRICE, DEV, and POP are shown above each node, with the ***x*** axis displaying the probability weight of each variable level. The contour lines shown for the MCC node represent levels of equal probability weights obtained by fitting Coupled Model Intercomparison Project Phase 5 data points (shown by black dots) to a bivariate normal distribution.

1,000 equal intervals by the same LHS scheme used for sampling (section 4.3). POP was represented by three discrete levels (low, medium, and high) that correspond to values of 1.6, 2, and 2.4 million and spanning the range of population levels projected by the Coastal Kenya Water Resources Management Authority up to the year 2032 (CES, 2014). MCC is a bivariate random node with 10^6 discrete levels from each unique combination of 1,000 mean temperature and precipitation changes.

The NPTs of the root nodes are the main entry points for belief information and represent the normalized probability weights assigned to the possible variable states. Figure 3 displays the contour lines that are used to weight the bivariate variable of mean temperature and precipitation changes. These contour lines were derived from the projected climate changes from the World Climate Research Programme Coupled Model Intercomparison Project Phase 5 multimodel ensemble. This was done by first calculating mean temperature changes from a total of 65 model runs between the future period of 2020–2070 and the historical period of 1950–2000 (shown by each point on Figure 3b). Next, these mean changes were fitted to a bivariate normal distribution:

$$P(\sim f, (\Delta TEMP, \Delta PRECIP)) = \frac{1}{(2\pi)^{\frac{k}{2}}|\Sigma|^{\frac{1}{2}}} \exp\left[-\frac{1}{2}(X-\mu)^T\Sigma^{-1}(X-\mu)\right], \tag{6}$$

where μ is the means and Σ is the covariance matrix of the mean annual temperature (°C) and precipitation changes (%), respectively. This bivariate distribution was then used to calculate the normalized probability weights of the discrete climate change levels considered in the analysis. In this work, we chose to weight the climate change uncertainty space using a generally well-known normal distribution, which was also used in several past Decision Scaling applications (Moody & Brown, 2013; Whateley et al., 2014). However, we recognize that the choice of a normal distribution can result in an undervaluation of extreme climate changes, and therefore, a fat-tailed distribution could be also preferred instead as shown by Taner et al. (2017). The subjective probabilities for the nodes DEV, POP, and EDR were set based on the outcomes of the stakeholder workshop held in August 2015. Based on stakeholder preference, the highest probability weights were given to medium levels for DEV and POP. For the EDR and DEM, most likely values are set to be as 2% and 1.3 m^3 per USD, respectively (Figure 3).

The NPTs for the two intermediate nodes SSY and PCD were derived using conditional truncated normal distributions, based on the opinions of the local experts during stakeholder/expert meetings. For example, the conditional probability distribution of specific sediment yield is defined as $P(SSY \mid DEV) \sim \psi(\overline{\mu}, \sigma^{-}, a, b; SSY)$, where $\overline{\mu}$ takes the values of 275, 325, and 375 $m^3 \cdot km^{-2} \cdot year^{-1}$ to reflect low, medium, and high economic development, respectively. This reflects the view that a higher level of economic development will result in a higher level of urbanization, which in turn will increase SSY at the upstream of the project site. Here, we could also link SSY to MCC (i.e., precipitation change) as increasing flood events is expected to increase sediment flux from the catchment area. However, we could not establish any meaningful relationship based on the empirical data and therefore neglected this link. Similarly, the conditional distribution of PCD is specified by shifting its mean based on the values of DEV, MCC, and PRICE, respectively. The mean of the distribution $P(PCD \mid DEV, MCC, PRICE)$ was set to increase with increasing economic development and increasing mean annual temperatures and decrease with the increasing price to reflecting the price elasticity domestic water consumption. The two random variables PCD and DEV, which are included in the Bayesian network but not in the LHS scheme, are used to calculate the normalized probability weights for the deterministic node, DEM. Overall, the probabilistic inference was made by calculating the posterior joint probability weight of each of the 1,000 SOWs and then normalizing to sum to unity.

4.4. Robustness Evaluation of the Design Alternatives

Finally, the posterior probability weights obtained from the BBN model were used to rank the alternatives based on their robustness. For comparing the value of the demonstrated framework, robustness is expressed in two ways by considering all possible outcomes as equally likely, and by weighting the outcomes based on the normalized probability weights from section 4.4.

5. Results and Discussion

In this section, we present the results for the water infrastructure design of the Mwache Dam in four sections. In section 5.1, we show the computed range of vulnerabilities from the four design choices concerning the reliability and NPV metrics. In section 5.2, we display the key factors affecting vulnerabilities from the regional sensitivity analysis. In section 5.3, we illustrate vulnerabilities for the water supply system in the cases of uniform and belief-informed weighting using multidimensional visualizations. Finally, in section 5.4, we compare the robustness of the four design alternatives with respect to the probabilistic weighting scheme and the performance metrics.

5.1. Vulnerabilities Associated with the Design Options

Figure 4 depicts the range of unacceptable performance outcomes for the four designs options with respect to the reliability and NPV-regret metrics. As noted in section 4.2, unacceptable performance is defined as less than 95% for reliability and more than US$ 10 million with respect the NPV-regret regret (in Figure 4, shown by the dashed lines in each panel). The relationship between reliability and design capacity size is monotonic, as larger alternatives always outperform the smaller options due to increased storage. For example, almost half of the simulation runs under the 80 MCM choice results in a failure, whereas the failures for

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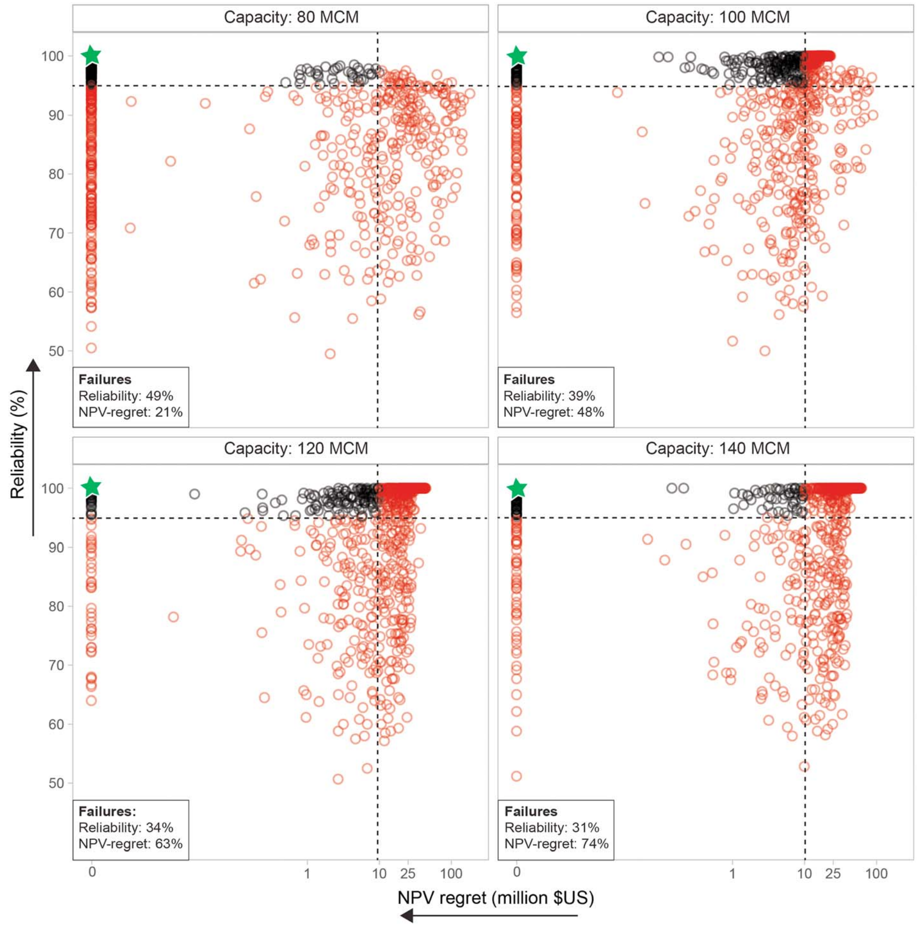

Figure 4. Vulnerabilities from the four design alternatives quantified according to the NPV-regret and reliability metrics. In each panel, the dashed lines indicate the thresholds that define acceptable and failure performance outcomes. The simulation runs with acceptable and failure performances are shown by the black and red circles. The star shows the ideal solution. NPV = Net Present Value.

the 120 MCM choice are only 31%. In contrast, it is seen that the smaller design choices (80 and 100 MCM) yield a nonacceptable NPV-regret over a small fraction of futures (21% and 41%, respectively), whereas larger choices (120 and 140 MCM) result in a substantially higher percentage of nonacceptable outcomes (63% and 74%, respectively). However, an interesting finding is that the magnitude of NPV-regret can be higher in the smaller design sizes (>US$ 100 million), whereas for the larger sizes they are more clustered within the US$ 5–25 million range.

5.2. Performance Sensitivity to Exogenous Uncertainty Factors

Figure 5 shows the relative importance of the six exogenous factors on the vulnerability of the four design options based on the results of the regional sensitivity analysis (see section 4.2). The relative importance of the factors depends on the metric used. Both reliability (Figure 5a) and NPV-regret (Figure 5b) metrics are sensitive to only a fraction of the input factors. For reliability, the most important factors are precipitation change (0.75) and demand level (0.5) across all four designs. In the case of NPV-regret, the result varies based on the preferred design size. An interesting finding is that a relatively smaller design size of 100 MCM is found to be highly sensitive to precipitation change (0.46), to a lesser extent to demand level (0.40), and insensitive to all the other factors. On the other hand, the two extreme choices (80 and 120 MCM) were found to be equally sensitive to Price (0.39) and discount rate (0.4). Specific sediment yield and temperature change were found insignificant for all design choices.

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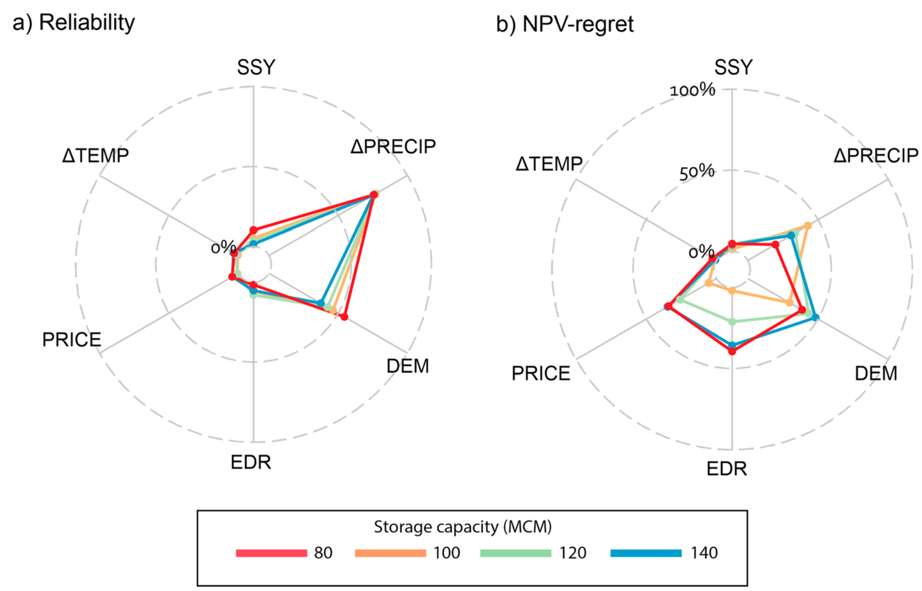

Figure 5. Regional sensitivity analysis results for the project vulnerabilities for (a) water service reliability and (b) NPV-regret. Larger values indicate greater sensitivity. SSY = specific sediment yield; ΔTEMP = change in temperature; PRICE = price charged for water use; EDR = economic discount rate; DEM = municipal water demand; ΔPRECIP = change in precipitation; NPV = Net Present Value.

5.3. Multivariate Visualization of Vulnerabilities Under Different Probabilistic Assumptions

In this section, the range of future conditions that may lead to the unacceptable reliability outcomes is highlighted using alluvial (or Sankey) diagrams (Schmidt, 2008). The results are visualized with respect to two probabilistic assumptions: a uniform weighting with the assumption that there is not sufficient information to distinguish the plausibility of one future state from another and a belief-informed weighting, where each future condition is weighted based on the corresponding normalized joint probability value obtained from the Bayesian network (section 4.3).

Figure 6 illustrates an alluvial diagram displaying the relationship between reliability and three key uncertainties explored (i.e., Δ*PRECIP*, *DEM*, and *SSY*) for the reservoir design capacity of 140 MCM. The data used in Figure 6 is prepared by first dividing the uncertainty range of each factor into a few "meaningful" categories (e.g., low, medium, and high), and then binning the stress test outcomes (1,000 data points) to those categories. Each alluvium (shown by as a stream on Figure 6) is then created based on the association of data in terms of the reliability metric (the left-most vertical axis) and the three key factors (shown on the remaining axes). On Figure 6, the width of an alluvium indicates the cumulative fraction of underlying data points within each category of a factor, as an indicator of its relative importance. When the data points are uniformly weighted (Figure 6a), there are six possible data patterns leading to an unacceptable reliability value, covering a total fraction of 0.31 of the total range. A large fraction of these unacceptable conditions is associated with a low precipitation level (from 10% to 50% decrease) and high demand level (from 80 to 100 MCM per year), with a cumulative weight of 0.19 out of 0.31. However, for the case of belief-informed weighting (Figure 6b), the cumulative probability of these six patterns leading to unacceptable reliability is only 0.06. Note that on Figure 6b, the low precipitation bin (50–90%) that is associated with most the failure outcomes has a very small value of marginal probability, reflecting the effects of GCM-driven belief information about the future climate. This finding shows that the belief information used to weight the outcomes provides an additional insight for decision-making, specifically to specify the level of concern associated with future vulnerabilities from not meeting the reliability target.

5.4. Robustness of Alternatives Under Different Probabilistic Assumptions

The final recommendation for the water supply system is made based on a comparison of calculated robustness values of the four engineering design choices with respect to the performance measures and the preferred way weighting of the explored future outcomes.

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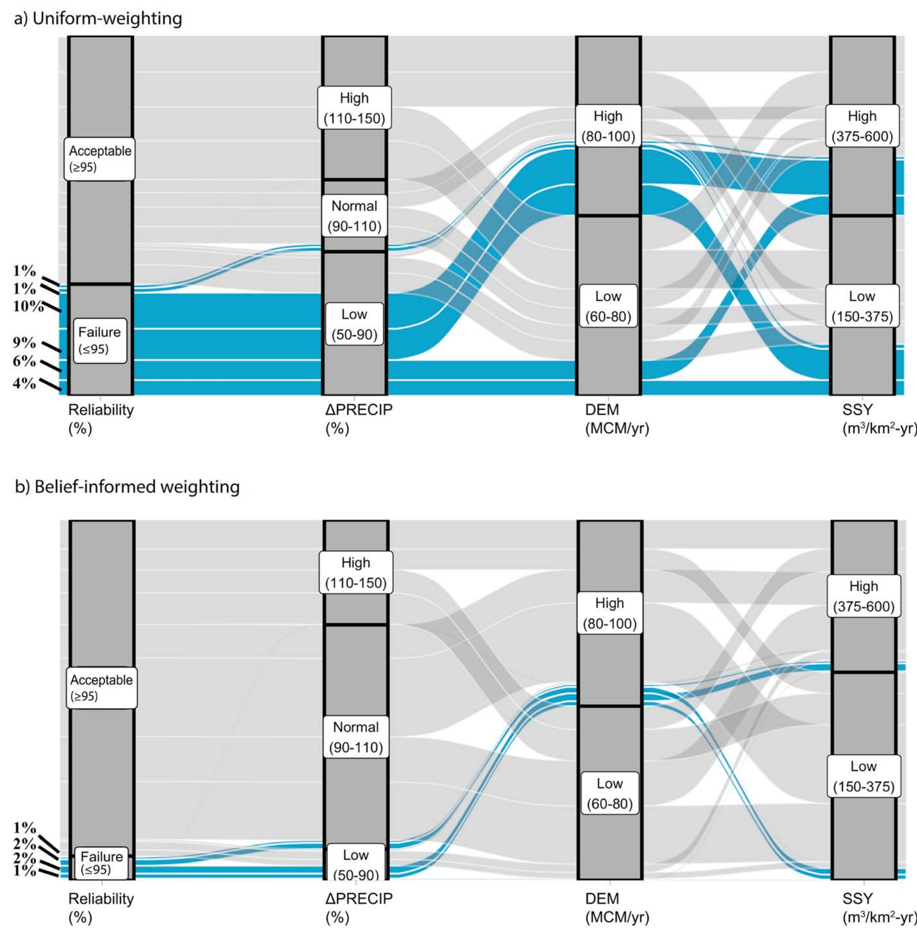

Figure 6. Alluvial diagrams depicting weighted vulnerabilities for the reliability metric ad the design capacity of 140 MCM. Results are shown with respect to (a) Uniform weighting and (b) Belief-informed weighting. The alluvia marked in blue colors represent the cumulative fraction of outcomes that fail to meet the desired reliability threshold of 95% under given conditions. Alluvia thickness increase with the fraction of observations in each category, with the weights assigned to each data points. The values indicated on the left of the plots depicts the weighted coverage of each alluvium as a percentage. ΔPRECIP = change in precipitation; DEM = municipal water demand; SSY = specific sediment yield.

Figure 7 shows the robustness of the design choices with respect to reliability and NPV-regret metrics under the uniform and belief-informed weightings. Robustness with respect to reliability increases with increasing storage capacity, with the most robust option being 140 MCM with robustness values 0.7 under the uniform-weighting and 0.92 under belief-informed weighting, respectively (Figure 7a). However, robustness with respect to NPV-regret displays a reversed ranking, in which smaller design alternatives are more preferable. With respect to robustness, the smallest design size (80 MCM) shows a robustness score of 0.8 under uniform weighting and 0.55 under belief-informed weighting (Figure 7b). For both metrics, it is seen that the weighting scheme did not affect the preference ranking, however, changed the scaling. The robustness range for the NPV-regret metric is substantially wider (0.2–0.8) under uniform weighting in comparison to the same metric range under belief-informed weighting (0.4 to 0.6). As the two robustness criteria point out the two extreme design choices, which is 140 MCM with respect to reliability and 80 MCM with respect to NPV-regret, the final judgment largely depends on the relative importance of each metric for the decision maker.

A further interesting information for the decision-makers is to show how much robustness one would sacrifice in terms of reliability to achieve a higher degree of NPV robustness. Figure 8 displays this information under uniform weighting and belief-informed weighting, respectively. When the vulnerability space is uniformly weighted, it is seen that the trade-offs between the two measures are relatively proportional across the four design choices. However, under the latter case of belief-informed weighting, it is

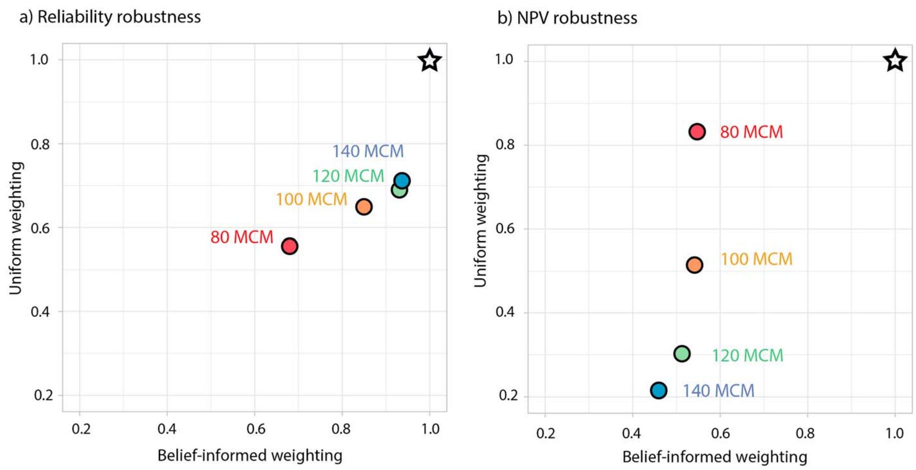

Figure 7. Robustness of alternatives with respect to the underlying probabilistic assumptions of uniform and belief-informed weightings: (a) Reliability metric and (b) NPV-regret metric. The star symbol indicates the location of the ideal solution. NPV = Net Present Value.

seen that with only a marginal loss in economic robustness, reliability robustness can be increased substantially. One can argue the larger design alternatives such as 120 or 140 MCM are particularly more favorable under the belief-informed weighting scheme due to the "flatness" of the trade-offs between reliability and NPV.

5.5. Final Remarks on the Integration of Probabilistic Information

The previous section demonstrates two strategies for probabilistic evaluation of system vulnerabilities under the four distinct reservoir design configurations. The former of these two is the more common uniform-weighting scheme, which applies the principle of insufficient reasoning, with the assumption that there is no basis to assign a higher probability weight to one possible outcome than another. The latter is belief-informed weighting, which represents our best effort to distinguish what we believe is more likely to occur over the future. The results under the belief-informed case incorporate into the risk-informing likelihood functions the richness of the most current scientific information (and the perspectives of credible experts) regarding the future in a way that the uniform-weighting scheme does not. Though we cannot know if one type of probability weighting scheme is more true of an unknowable future than the other, we can

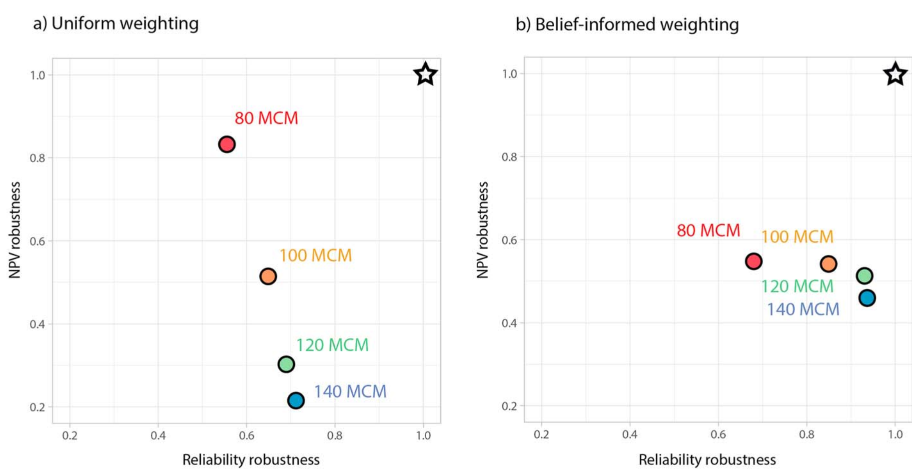

Figure 8. Robustness trade-offs of the alternatives with respect to NPV-regret and reliability metrics: (a) Under uniform weighting and (b) Under belief-informed weighting. The star symbol indicates the location of the ideal solution. NPV = Net Present Value.

use BNDS to explore the impacts on the decision of many plausible PDFs of many relevant classes of future conditions and trade them off against each other in a posterior sensitivity analysis. BNDS offers flexibility to respond to one of the most fundamental precepts of deep uncertainty, that informed stakeholders may disagree on the proper PDF for future conditions, by quantitatively evaluating whether it is worthwhile to spend time on the disagreement (and refine the probabilities), or to move on to matters of greater consequence.

6. Conclusions

This paper develops a novel approach that bridges a scenario-neutral vulnerability analysis with a multidimensional likelihood assessment to support robust water resources planning across long time scales. The coupled approach first uses exploratory modeling to evaluate a water resources system considering a wide range of climatic, demographic, and financial uncertainties and identifies possible futures conditions that lead to vulnerable outcomes with respect to the performance metrics and thresholds specified. A BBN then assimilates best available beliefs about the future conditions from multiple sources including historical data, model projections, stakeholder elicitations, or similar. In this process, the BBN sets the conditional dependency relationships among distinct classes of uncertain factors and provides a multivariate joint probability distribution of possible futures conditional on the imprecise information assimilated. The results of the BBN are then used to assess the relative likelihoods of vulnerable outcomes and finally calculate a belief-informed robustness score.

The presented approach builds upon the existing decision scaling approach and makes several improvements. First, the adopted probabilistic network approach allows stakeholder beliefs and local information to be quantified and incorporated into the risk assessment process and strengthens the “bottom-up” nature of the analysis. Stakeholder participation is not only limited to the first phase of project characterization, for example, the definition of performance thresholds, but also at the final phase of risk analysis and scenario definition. Second, the framework allows the blending of multiple sources of information in a coherent probabilistic framework way, which helps analysts to rapidly test the implications of divergent probabilistic assumptions about the future.

The separation of “vulnerability analysis” and “likelihood assessment” phases is of fundamental importance to the work. By beginning with the sensitivity analysis as the means of vulnerability assessment, a complete exploration of vulnerabilities is possible, and the risk is avoided that key vulnerabilities with very low probabilities will be missed. BNDS provides a full representation of the system response to uncertain factors, which in many cases is useful in its own right. In addition, stakeholders are generally uneasy with an analysis that requires initial estimations of probabilities, as they rightly recognize (1) they are ill-placed to make or judge such estimations and (2) the results are highly dependent on the choices. For these reasons, a diverse set of stakeholders will often disagree strongly about such required estimations.

There are several directions for future work. One potential use of the BNDS framework is to explore the robustness of decisions under a wide range of subjective probability distributions derived from distinctive worldviews of the experts or model outcomes. In doing this, the analyst can identify dominating solutions, that is, solutions that are less sensitive to probabilistic assumptions. In most cases, we think using multiple belief distributions may be more useful in addressing the deep climate and socioeconomic uncertainties faced in water resources systems, where experts can almost never agree upon the subjective probabilities of possible outcomes. A second direction for the future research is to combine the BNDS framework with scenario discovery to obtain few, lower-dimensional scenarios that better reflect stakeholder beliefs (see Bryant & Lempert, 2010). This requires further developing of existing classification methods such as the Patient Rule Induction Method or the Classification and Regression Trees (Lempert et al., 2008) to account for the probabilistic information about the uncertain factors considered. We are currently working on a modified Patient Rule Induction Method methodology that would be able to provide this additional information. Finally, although the presented work advances the existing decision-scaling methodology, the demonstrated procedure of combining vulnerability analysis with probability distributions can be easily applied to the other methods of decision making under deep uncertainty such as Robust Decision Making.

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