

Water Resources Research

RESEARCH ARTICLE

10.1002/2015WR018164

Key Points:

- Estimated the probability of water restrictions under nonstationary climate
- Identified water plans that meet tolerable risk criteria
- Demonstrated sensitivity of plans to risk criteria and model uncertainties

Supporting Information:

- Supporting Information S1

Correspondence to:

E. Borgomeo,
eduardo.borgomeo@ouce.ox.ac.uk

Citation:

Borgomeo, E., M. Mortazavi-Naeini, J. W. Hall, M. J. O'Sullivan, and T. Watson (2016), Trading-off tolerable risk with climate change adaptation costs in water supply systems, *Water Resour. Res.*, 52, 622–643, doi:10.1002/2015WR018164.

Received 28 SEP 2015

Accepted 4 JAN 2016

Accepted article online 7 JAN 2016

Published online 1 FEB 2016

Corrected 2 NOV 2016

This article was corrected on 2 NOV 2016. See the end of the full text for details.

Trading-off tolerable risk with climate change adaptation costs in water supply systems

Edoardo Borgomeo¹, Mohammad Mortazavi-Naeini¹, Jim W. Hall¹, Michael J. O'Sullivan², and Tim Watson³

¹Environmental Change Institute, University of Oxford, Oxford, UK, ²Engineering Science, University of Auckland, Auckland, New Zealand, ³ICS Consulting Ltd., Little Smeaton, UK

Abstract Choosing secure water resource management plans inevitably requires trade-offs between risks (for a variety of stakeholders), costs, and other impacts. We have previously argued that water resources planning should focus upon metrics of risk of water restrictions, accompanied by extensive simulation and scenario-based exploration of uncertainty. However, the results of optimization subject to risk constraints can be sensitive to the specification of tolerable risk, which may not be precisely or consistently defined by different stakeholders. In this paper, we recast the water resources planning problem as a multi-objective optimization problem to identify least cost schemes that satisfy a set of criteria for tolerable risk, where tolerable risk is defined in terms of the frequency of water use restrictions of different levels of severity. Our proposed method links a very large ensemble of climate model projections to a water resource system model and a multiobjective optimization algorithm to identify a Pareto optimal set of water resource management plans across a 25 years planning period. In a case study application to the London water supply system, we identify water resources management plans that, for a given financial cost, maximize performance with respect to one or more probabilistic criteria. This illustrates trade-offs between financial costs of plans and risk, and between risk criteria for four different severities of water use restrictions. Graphical representation of alternative sequences of investments in the Pareto set helps to identify water management options for which there is a robust case for including them in the plan.

1. Introduction

A great challenge for infrastructure planning and natural resources management under climate change is to determine the level of adaptation investment that is proportionate to the climate-related risks a particular system is facing [Hall *et al.*, 2012a]. This is particularly true in the water sector, where the impacts of climate change and the costs of adaptation investments in new and existing infrastructure are going to be significant [European Environment Agency, 2007; Hughes *et al.*, 2010; U.S. Environmental Protection Agency, 2012].

Traditional water resources planning approaches, based on linear programming models [e.g., Lund and Israel, 1995; Randall *et al.*, 1997] and least cost capacity expansion [e.g., Braga *et al.*, 1985], are not well suited to respond to this challenge because they only consider a single objective (cost minimization subject to some deterministic target/constraint), are based on historical observations, and do not require water managers to explicitly state their attitude toward *risk* [Reed and Kasprzyk, 2009] (italicized terms are defined in Appendix A). Least cost optimization methods, if not accompanied by sensitivity and *robustness analysis*, can identify solutions that are vulnerable to uncertainty and are bound to yield suboptimal performance if the future differs from expectations [Ben-Haim, 2006]. Although the limitations of least cost optimality have been recognized for a long time [Liebman, 1976], in practice, many water planners around the world still use least cost optimization to select their *water resources management plans* and justify their investments. For instance, the 2014 water resources management plans developed by water utilities in England are based on a single-objective least cost optimization approach [UKWIR, 2002; Padula *et al.*, 2013], which does not consider *trade-offs* between multiple objectives, and does not include any explicit characterization of the risks associated with delivering the proposed plans [Hall *et al.*, 2012b; Matrosov *et al.*, 2013a].

There has been extensive research to address the limitations of least cost planning approaches [e.g., Kasprzyk *et al.*, 2013; Herman *et al.*, 2014; Brown *et al.*, 2015]. This has focused upon the role of uncertainty, in

particular, in hydrological variability and future *climate projections* [e.g., Ray *et al.*, 2012]. Research has sought to test the sensitivity of alternative plans to uncertainties in future climate conditions, through decision-scaling [Brown *et al.*, 2011, 2012; Moody and Brown, 2012; Turner *et al.*, 2014; Whateley *et al.*, 2014; Poff *et al.*, 2016], robust decision-making [e.g., Groves and Lempert, 2007; Kasprzyk *et al.*, 2013; Herman *et al.*, 2014], info-gap [Korteling *et al.*, 2013; Matrosov *et al.*, 2013b], and vulnerability-based approaches [e.g., Nazemi *et al.*, 2013; Nazemi and Wheeler, 2014; Singh *et al.*, 2014]. These methods seek to identify plans that are *robust* to a wide range of possible future conditions. Robustness to future uncertainty can be enhanced by building flexibility into future plans, which can be appraised using real options analysis [Steinschneider and Brown, 2012; Jeuland and Whittington, 2014].

The inherently stochastic nature of hydrology means that water resources planning lends itself to being cast as a reliability problem [Hashimoto *et al.*, 1982]. Reliability analysis quantifies the probability of failed states of a system; reliability-based planning seeks to maintain the failure probability at a tolerable level. That however begs the question of what the tolerable failure probability might be. Unlike conventional reliability theory, water resource system failure is not a binary problem. When water is scarce, different users of water within a basin experience shortages of varying severity or may have restrictions imposed upon the amount of water they are permitted to withdraw. The natural environment may also be impacted. The planning problem therefore involves evaluating and trading-off these multiple impacts with the costs of reducing their likelihood and severity. Hydroeconomic modelers [e.g., Harou *et al.*, 2009] have sought to quantify the impacts, for example, of reduced agricultural or hydropower production in economic terms using computable general equilibrium models [Horridge *et al.*, 2005; Logar and van den Bergh, 2013].

Combining stochastic analysis of water shortages with economic quantification of impacts enables the quantification of the risk of water shortages and, in principle at least, fully *risk-based decision-making* in which the benefits of risk reduction are compared with the cost of intervention in the system. However, the approach is still plagued by the effects of hydrological and climatic uncertainties that have already been mentioned, on top of which are layered the uncertainties in quantification of economic consequences of water shortages and restrictions. The latter problem is particularly acute in the case of urban water supplies, which will tend to be prioritized in times of water scarcity because of the potential for major economic and societal disruptions. Severe restrictions on water use in urban areas are therefore rare, for example, not having occurred extensively in the UK since 1976 [Marsh *et al.*, 2007]. This means that the empirical evidence of the economic impacts of urban water restrictions is very scarce. Studies that have sought to quantify the economic impacts of severe water restrictions (e.g., in London, estimated to be 236–330 million British pounds per day [Lambert, 2015]) have been based upon bottom-up analysis of the consequences of different types of hypothetical impact. Given the difficulty of directly quantifying economic impacts, regulatory arrangements for water utilities have focused upon water users' stated preferences and willingness to pay to avoid restrictions of differing severity [e.g., Lund, 1995; Hensher *et al.*, 2006].

Users of water have different attitudes to restrictions on water use at differing levels of severity. They tend to be particularly averse to the most severe water rationing. The water resources planning problem needs to take into account water users' attitudes to risk at the full range of levels of severity, alongside the costs associated with reducing the frequency of water restrictions. This therefore represents a multiobjective decision problem, in which *tolerable risk* criteria (for impacts of differing levels of severity) are traded off against *financial costs* of water resources management plans. As noted above, if the impacts of restrictions on water use could be accurately quantified in economic terms then the problem could be converted into a single-objective optimization problem. However, explicitly dealing with multiple objectives overcomes the need to monetize the very complex impacts of water shortages and restrictions and makes the trade-offs between different levels of risk and cost explicit.

Significant attention has been devoted to developing multiobjective optimization methods for water resources planning [e.g., Kasprzyk *et al.*, 2009; Mortazavi *et al.*, 2012; Giuliani *et al.*, 2014], which we adapt here to the challenge of exploring the trade-offs between risk and financial costs of alternative water management plans. We argue that this is necessary in order to make proportionate adaptation decisions that identify water resources investments capable of cost-effectively reducing risks. We thus address the need for climate change adaptation approaches that involve iterative risk management processes and that take explicit account of decision-makers' attitudes toward risks [OECD, 2013; IPCC, 2014a].

In this paper, we demonstrate how framing the adaptation investment problem in terms of trade-offs between financial costs and tolerable risks allows water managers to address the question: "Which course of action will result in tolerable risk and how much will it cost to achieve tolerable risk?" In trying to answer this question, we propose a decision-making framework to explicitly evaluate risks and explore the implications of choices for risk tolerability on the selection of adaptation *options* and associated financial costs.

To identify the implications of different levels of tolerable risk on the selection of alternative adaptation options and their financial costs, we employ a multiobjective optimization approach using evolutionary algorithms. Evolutionary algorithms have found an enormous variety of applications in water resources [Nicklow *et al.*, 2010; Reed *et al.*, 2013; Maier *et al.*, 2014] including: water mains replacement planning [Dandy and Engelhardt, 2006]; portfolio planning of urban supply systems [Kasprzyk *et al.*, 2009]; reliability-based optimization of water distribution systems [Tolson *et al.*, 2004]; water reservoir operations [Giuliani *et al.*, 2015]; and long-term groundwater monitoring [Reed and Minsker, 2004]. More recently, multiobjective evolutionary algorithms have been used for water resources planning problems under uncertainty, for instance, to map out robustness trade-offs associated with regional cooperative water resources planning under deep uncertainty [Herman *et al.*, 2014], to incorporate adaptation and mitigation responses in urban water supply planning [Paton *et al.*, 2014a], to schedule capacity expansion [Mortazavi-Naeini *et al.*, 2014], and to determine the optimal sequencing of urban water supply infrastructure [Beh *et al.*, 2014, 2015].

The aim of this study is to present and demonstrate a method to identify trade-offs between financial costs of adaptation in water supply systems and the probability of exceeding the *target frequency of water restrictions* of different levels of severity. Our method differs from previous applications of multiobjective evolutionary algorithms and robust optimization methods to water planning problems because previous approaches [e.g., Ray *et al.*, 2014; Mortazavi-Naeini *et al.*, 2015b] quantify water system performance in terms of reliability with respect to a range of stochastic inputs conditioned on historical observations, whereas our study seeks to trade-off financial costs of adaptation with changing levels of risk over the planning period, where changing risk is driven by nonstationary climate model inputs. Furthermore, previous applications of multiobjective algorithms to water resources decision-making under uncertainty [e.g., Kasprzyk *et al.*, 2013; Herman *et al.*, 2014, 2015; Matrosov *et al.*, 2015] explore trade-offs between alternative water management options and their robustness to uncertainty without focusing on the trade-offs between financial costs of water resources management plans and *risk attitudes* toward water restrictions of different levels of severity, which is the main focus and contribution of this study.

We recognize that risk-based decisions rely on the quantification of uncertainties in probabilistic terms, which may provide a false sense of security and misrepresent climate change uncertainty [Hall, 2007; Stainforth *et al.*, 2007]. In particular, the quantification of climate uncertainty in probabilistic climate projections does not consider all sources of climate uncertainty and is also conditional on a range of climate modeling choices and assumptions [Brown and Wilby, 2012]. Climate model projections are typically conditional upon a given emissions scenario, though, over the planning time scale of 25 years that is considered in the case study presented here, there is very little noticeable difference between emissions scenarios, so almost all of the climate uncertainty is attributable to model uncertainties and internal climatic variability. The climate modeling community is increasingly seeking to express climate model uncertainties in probabilistic terms, notably in the IPCC's fifth Assessment Report [IPCC, 2014b] and the UK's UKCP09 downscaled climate projections [Murphy *et al.*, 2009]. Thus, the challenge for impacts modelers and decision-makers is to make use of these probabilistic statements (which potentially provide important information that could improve decision-making) whilst being very aware of the uncertainties and extensively testing the sensitivity of their decisions to those uncertainties. These considerations do not undermine the proposed approach, instead highlighting the need for decision-making frameworks where all available evidence on future uncertainties can be collected, where the impact of these uncertainties on decision-relevant metrics can be evaluated and where new information can be incorporated as it becomes available.

We emphasize that analysis of water security risks under climate change should be accompanied by robustness analysis [e.g., Moody and Brown, 2013; Matrosov *et al.*, 2013b; Nazemi *et al.*, 2013; Korteling *et al.*, 2013; Borgomeo *et al.*, 2015a, 2015b] that examines the sensitivity of selected plans to assumptions (e.g., constant interannual variability) and residual uncertainties. The complex problem of climate change adaptation in water supply systems will benefit from a two-pronged approach that couples risk-based approaches incorporating available probabilistic evidence from climate models with sensitivity and robustness analysis.

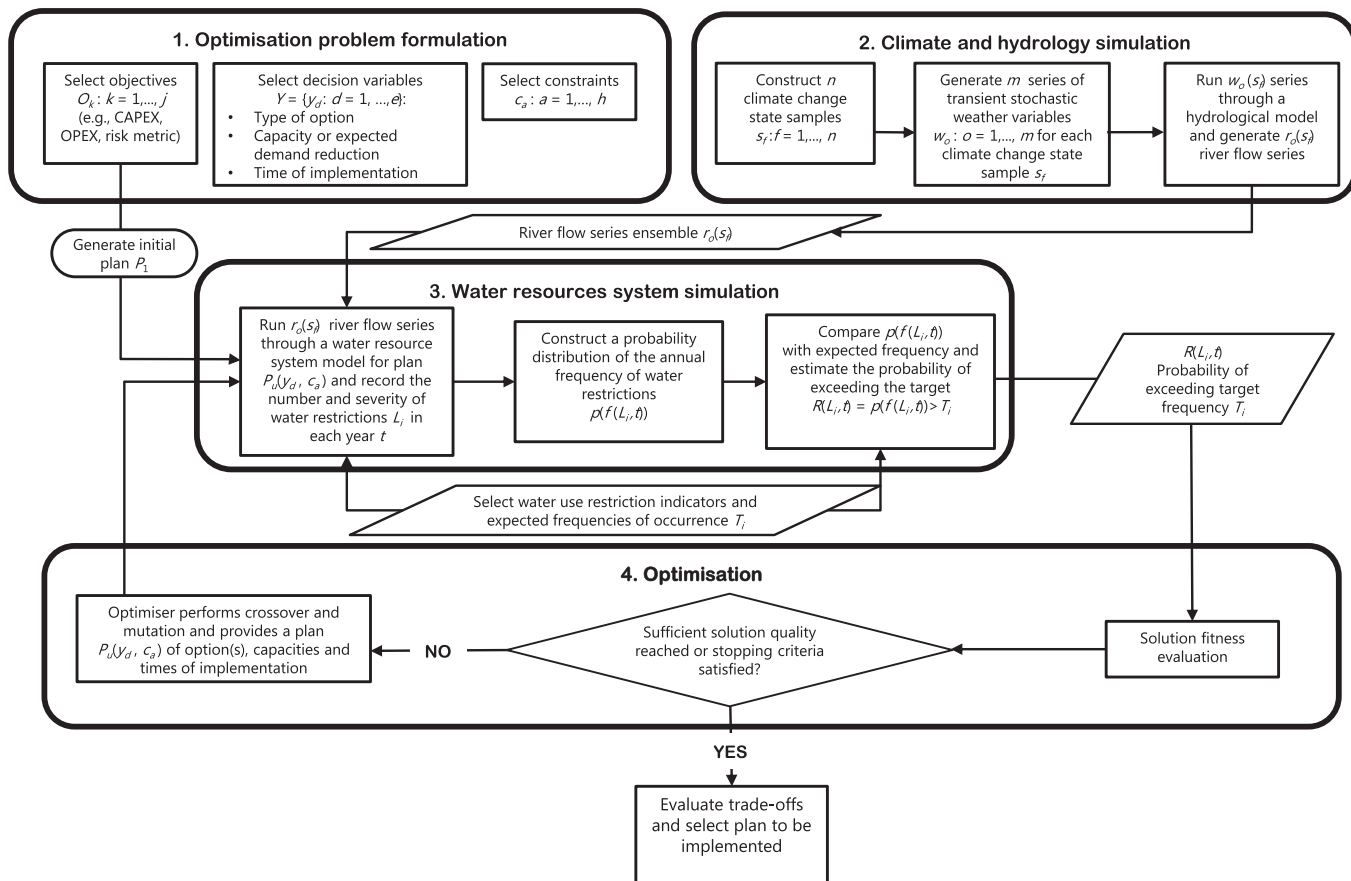


Figure 1. Flowchart of the risk-based optimization framework. CAPEX and OPEX stand for capital and operational expenditures, respectively. Å

The next section describes the methods that combine a probabilistic decision-making framework with optimization using evolutionary algorithms. Section 3 presents the case study area, the modeling framework and then describes the optimization formulation and the planning alternatives considered in the optimization problem. Section 4 reports the results from the case study application. A discussion of the case study's results and limitations of the method is presented in section 5.

2. Methods

2.1. Optimization Problem Formulation

Analyzing and selecting water resources management plans requires formulation of a utility function, which articulates preferences and attitudes to risk. Thus, in the first step of our risk-based optimization (box 1 in Figure 1), water managers specify a vector of objectives \mathbf{O}_k , $k = 1, \dots, j$. In the context of climate change adaptation in water supply systems, objectives include (i) minimizing the financial costs associated with operating the system, building new infrastructures, or delivering a leakage reduction plan [e.g., Ray et al., 2012] and (ii) minimizing a risk metric defined as the probability of specified potentially harmful events occurring, estimated with the methods presented in section 2.2. Other objectives, not considered in this paper, may seek to minimize other impacts, for instance, on ecosystems. As demonstrated in previous applications of multiobjective evolutionary algorithm frameworks in water resources planning problems, the selection of the objectives can extend beyond traditional cost and reliability metrics, to include objectives such as minimizing GHG emissions [Wu et al., 2013; Paton et al., 2014a], minimizing alterations to flow [Hurford et al., 2014], or minimizing financial risk [Zeff et al., 2014].

Alongside the objectives \mathbf{O}_k , a set of decision variables $Y = \{y_d: d = 1, \dots, e\}$ need to be specified before the search starts. For water supply systems, the decision variables to be optimized include the type of

Table 1. Water Use Restrictions of Different Levels of Severity and Relative Demand Savings^a

Level of Service (L_i)	Frequency of Occurrence (T_i)	Water Use Restrictions	Expected Demand Reduction (Cumulative)
Level 1	1 year in 5 on average	Intensive media campaign	2.2%
Level 2	1 year in 10 on average	Sprinkler/unattended hosepipe ban, enhanced media campaign	9.1%
Level 3	1 year in 20 on average	Temporary use ban (formerly hosepipe ban)	13.3%
Level 4	1 year in 200 on average	Emergency Drought Order for standpipes and rota cuts	31.3%

^aThe Levels of Restrictions correspond to the storage levels shown in Figure 2 [from *Thames Water*, 2014].

option (e.g., storage, water reuse, leakage reduction plan) considered feasible by the water managers, the time of implementation, and the expected yields of supply sources or expected water savings from demand-side options. Decision variables could be extended to also include operating rules, decision triggers, or nonconventional supply sources, such as storm water harvesting schemes or household rainwater tanks [e.g., Paton *et al.*, 2014b].

A vector of constraints \mathbf{c}_a , $a = 1, \dots, h$ could also be specified to restrict the search. For instance, constraints may need to be applied to guarantee minimum performance in the selected water resources management plans, to ensure that the optimizer does not implement mutually exclusive options in the same plan, or to represent financial constraints. Given particular constraints and decision variables, the optimizer provides a water resources management plan P_u , $u = 1, \dots, v$. The optimizer designs a plan by combining the decision variables and taking into account the constraints. The plans generated by the optimizer will differ in terms of the type of option, capacity, time of implementation, and financial cost.

2.2. Metrics of Tolerable Risk

Each water resources management plan P_u , generated by the optimizer according to the objectives and constraints specified in the formulation is evaluated over a range of future climate projections using the risk-based approach developed by Borgomeo *et al.* [2014]. This probabilistic framework couples climate and hydrological simulations with water resource system simulations to estimate the probability of exceeding a target frequency of water restrictions under nonstationary climate conditions.

The framework seeks to estimate the frequency of occurrence of particular observable undesired outcomes of the water resource system, notably water use restrictions, which may range in severity from restrictions on nonessential uses of water through to severe cuts to domestic supplies. The impacts of these restrictions have been estimated from a variety of perspectives, including "bottom-up" economic impacts assessment and willingness to pay surveys of water users [Lund, 1995]. Willingness to pay surveys explore water users' attitudes to the frequency with which restrictions of different levels of severity may be imposed. These surveys therefore effectively explore the tolerability of the risk of water restrictions, which is articulated in terms of the maximum frequency for restrictions of given levels of severity. Also of relevance are water managers' attitudes to risk, which may include concerns about reputational impacts for the water utility of imposing restrictions on water use.

The target frequency of a water use restriction may seem a counterintuitive measure of system performance, because water managers always seek to minimize service disruptions and satisfy water demands. However, water managers widely accept the notion that it is impossible to achieve 100% reliability in water supplies, given inherent hydrological variability. The Levels of Service that water utilities agree to provide to their water users, which are expressed in terms of target frequencies of water restrictions, explicitly incorporate this notion that it is neither possible nor cost effective to reduce the probability of water restrictions to zero. An example of these target frequencies of restrictions for four different Levels of Service defined by London's water utility is shown in Table 1.

Given a stationary climate, constant water demands, and extensive observations of system performance, it would in principle be possible to estimate precisely the frequency of water restrictions in a water supply system. In practice, we recognize the effects of nonstationary hydrology, alongside many other factors that are leading to change within the system. All of these factors are uncertain, to a greater or lesser extent, so we cannot precisely estimate the frequency with which water restrictions will occur. Given probabilistic

estimates about some of these uncertainties—for instance, uncertainties about climate change that are being quantified by large ensemble experiments with climate models [Murphy *et al.*, 2007; Murphy *et al.*, 2009]—it is, however, possible to estimate the probability of exceeding target frequencies of water restrictions. These probabilistic estimates are conditional on a set of climate modeling methodological choices and assumptions which require extensive robustness analysis to unmodeled uncertainties (e.g., such as changes in interannual variability under climate change [Steinschneider *et al.*, 2015]), as discussed in section 1. The probability of exceeding the target frequency of water use restrictions associated with one or more Levels of Service is the risk metric that we have used in our assessment of the water supply system [Hall *et al.*, 2012b; Borgomeo *et al.*, 2014].

While our risk metric is expressed in terms of the probability of exceeding a Level of Service target frequency, this metric implicitly contains quantification of the consequences. It would be possible to replace this probability metric with an estimate of expected economic loss, but that would be of less direct relevance to the metrics that are used in the water resources planning process. This risk metric based on frequencies of restrictions of different severities is, therefore, included as an objective in the optimization for two reasons. First, water managers in the UK and elsewhere (e.g., in the USA [Zeff *et al.*, 2014]) have expressed the need to control the frequency with which restrictions are imposed on water users to avoid unpopular measures and negative impacts on economic activities. Thus, by trading-off the probability of exceeding a target frequency of restrictions with financial costs required to reduce that probability, our approach is relevant to decision-making and responds to decision-makers' needs in terms of understanding how alternative options and associated costs influence frequencies of restrictions in their systems. Second, we include risk metrics based on frequencies of restrictions instead of metrics based on expected economic losses because of the difficulties in estimating the latter [Mortazavi *et al.*, 2012] and the general lack of sufficient information on expected costs of water restrictions. Furthermore, we note that a single-objective optimization based on minimizing expected losses which treated the risk metric as a constraint would not allow water managers to fully explore the trade-offs between their plans' financial costs and the probability of exceeding the target frequency of water restrictions of different levels of severity. Given that the impacts of restrictions of different severities are different, a multiobjective problem formulation is also appropriate to understand whether minimizing the risk metric for a low severity restriction comes at an excessively high cost without reducing the risk metric for higher severity restrictions.

2.3. Simulation Framework

Our approach to estimating the probability of exceeding a target frequency of water restrictions is based on simulation of multiple possible realizations of future monthly nonstationary hydrological series, which are input to a water resources system model. Each simulation is conditioned on a future possible state of the climate based on a large ensemble of possible future climate projections [Borgomeo *et al.*, 2014]. This repeated stochastic simulation approach enables sampling of a wide range of possible hydrological conditions and extensive analysis of future climate uncertainties within a probabilistic framework. A similar approach based on extensive stochastic simulation of hydroclimatic variables to inform climate risk assessments in water supply systems has been proposed by Steinschneider and Brown [2013].

To estimate the risk metric for each water resources management plan P_u generated by the optimizer, we construct n samples s_f , $f = 1, \dots, n$ representing different future states of the climate (box 2 in Figure 1). These climate change states describe possible future evolutions of the climate conditions in the area of interest and can be defined using change factors from climate models or other scenarios of hydroclimatic change based on paleoclimate or historical information [e.g., Tingstad *et al.*, 2014; Patskoski and Sankarasubramanian, 2015].

For each s_f , m transient stochastic series w_o , $o = 1, \dots, m$ of relevant weather variables (e.g., rainfall, temperature) are generated. These series represent stochastic realizations of the same climate state and allow us to incorporate the uncertainty around natural variability in the analysis. Transient stochastic weather generators of the type described by Burton *et al.* [2010] and Glenis *et al.* [2015] could be used to perform this task. The sequences $w_o(s_f)$ are run through a hydrological model to generate $r_o(s_f)$ sequences of river flows and/or groundwater levels. Uncertainty arising from hydrological model parameters and structure could be incorporated in this framework as illustrated by Borgomeo *et al.* [2014].

The flows $r_o(s_t)$ are run through a water resource system simulator and the number and severity i of water restrictions L_i occurring in each year t of the simulation is recorded (box 3 in Figure 1). The frequency $f(L_i, t, n)$ of water restrictions in each year t for each climate scenario sample n is estimated by dividing the number of stochastic realizations where a restriction occurs by the total number of realizations m . By combining the $f(L_i, t, n)$ calculated for each n sample, we construct a probability distribution $p(f(L_i, t))$ of the frequency of water restrictions for each year t .

The probability distribution $p(f(L_i, t))$ of the frequency of water restrictions is compared with the target frequency T_i expressed in the Level of Service to estimate the probability $R(L_i, t)$ of exceeding the Level of Service frequency for each plan P_u for each year t in the simulation. $R(L_i, t)$ is estimated as the proportion of realizations m which exceed the target T_i in year t for a water restriction of severity L_i , that is, the total number of realizations m which fail to meet the Level of Service. In mathematical terms, if $F_{p(f(L_i, t))}$ is the cumulative distribution of $p(f(L_i, t))$, then $R(L_i, t)$ is estimated as [Hall et al., 2012b]:

$$R(L_i, t) = 1 - F_{p(f(L_i, t))}(T_i) \quad (1)$$

2.4. Optimization and Trade-Off Evaluation

For each run of the water resources system model, the optimizer evaluates each water resources management plan's P_u performance (box 4 in Figure 1) with respect to the objectives specified in box 1. These objectives include the combined operational and capital costs of each plan P_u and the risk metrics $R(L_i, t)$ calculated in boxes 2 and 3 for each of the different levels of restrictions L_i and for each year of the planning period. For each level of restriction L_i , the optimizer selects the maximum value of $R(L_i, t)$ across the entire planning period. This means that the optimizer minimizes the maximum probability of exceeding the target frequency experienced during the simulated planning period. By including the maximum risk value across the planning period in the objective function, we optimize against the worst outcome, in terms of exceeding the target frequency, in the simulations. The tolerability around $R(L_i, t)$ may change depending on the water manager's risk attitude and also on the severity of the water restriction in question. For instance, water managers may be willing to accept a higher probability of exceeding their target frequency for low severity water restrictions (i.e., hosepipe bans) than for high impact, high severity water restrictions involving supply interruptions and water rationing.

By generating trade-offs between financial costs and the probability of exceeding target frequencies for different levels of water restrictions, our approach shows how plans may change under different risk attitudes for different severities of water use restrictions.

The optimization search lends itself to application of multiobjective evolutionary algorithms as they have a proven ability to solve complex water resources planning problems [Mortazavi-Naeini et al., 2015a] and can accommodate multiple objectives and constraints without requiring prior preferences to be specified by the decision-makers [Herman et al., 2015].

3. Case Study

The framework described in section 2 was applied to London's water supply system. The purpose of this case study is to demonstrate how our method can be used to explore trade-offs between financial costs and probability of exceeding a target frequency of water restrictions of four different levels of severity.

3.1. Background

The London urban water supply system is located in the Thames basin, south-east England. This basin has been classified as water stressed and is experiencing high population growth [Environment Agency, 2013]. Climate change impact assessments indicate that water availability in the Thames basin may decrease as a result of climate change [Diaz-Nieto and Wilby, 2005; Manning et al., 2009].

Water supply in the study area is managed by Thames Water, a privately owned water utility serving approximately 7 million customers in the city of London alone. Every 5 years Thames Water, in compliance with national water planning regulations, produces a water resources management plan where it presents the actions it will take in the next 25 years to balance supply and demand. In its 2014 water resources management plan, Thames Water used a least cost deterministic optimization model to identify the preferred plan capable of maintaining the supply-demand balance [UKWIR, 2002; Padula et al., 2013]. In addition,

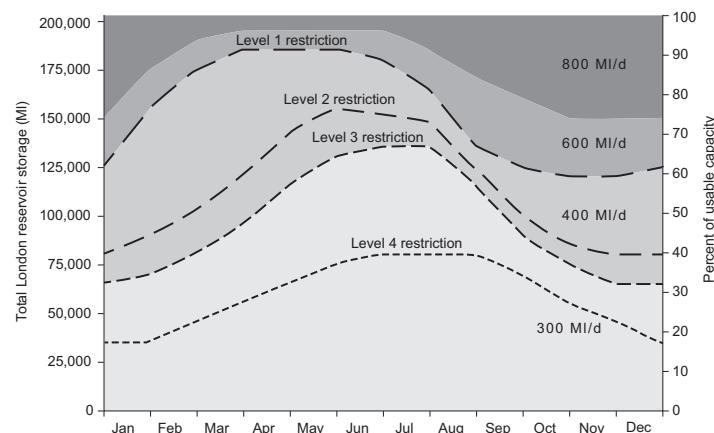


Figure 2. Lower Thames Control Diagram showing four restriction levels resulting in the restrictions shown in Table 1 and target environmental releases.

water sources. Most urban demands are met with surface water from the reservoirs, with supply from groundwater sources satisfying the remaining demands. The water supply system also relies on a few supply infrastructures that are activated only at times of drought. These include a 150 ML/d desalination plant and two groundwater sources, capable of supplying 130 and 66 ML/d [Thames Water, 2014].

River abstractions and reservoir operations are regulated by the Lower Thames Operating Agreement (LTCD), which defines the maximum abstraction limits and the minimum downstream target environmental flows. The target environmental flows are defined as a function of the total storage capacity in the reservoirs as shown in Figure 2. As reservoir levels drop, the downstream target environmental flow is reduced allowing for more water to be used for public water supply. The storage curves in the LTCD also define the different levels of water use restrictions imposed on customers. Progressively more severe water use restrictions are imposed on water users as storage levels drop. For each restriction level, the water utility has established a target frequency of occurrence, as shown in Table 1. These target frequencies of occurrence define the Level of Service the water utility agrees to provide to its customers. In the UK, context Levels of Service are defined based on frequencies of occurrence only, without consideration of the duration of water restrictions. The duration of restrictions could also be estimated from the simulation methodology described here and incorporated as another metric in the decision problem [e.g., Mortazavi *et al.*, 2012].

3.2. Modeling Setup

The climate states for the case study area were defined using the UKCP09 projections coupled with a transient stochastic weather generator [Glenis *et al.*, 2015]. The UKCP09 projections provide probability distributions of change factors measuring changes in relevant weather variables (temperature and precipitation) with respect to the 1961–1990 baseline climatology [Murphy *et al.*, 2009] for a medium emission scenario. The UKCP09 projections were generated from a large perturbed physics ensemble of the Met Office Hadley Centre's HadCM3 GCM. A Bayesian framework was used to characterize climate model uncertainty in the UKCP09 projections based on the model skill at reproducing observed climate variables but also incorporating results from a multimodel ensemble to quantify climate model structural error. More details on the UKCP09 projections and the Bayesian uncertainty estimation framework can be found in Murphy *et al.* [2007, 2009]. These probabilistic projections are conditional upon a given emissions scenario. Given a 25 years planning horizon, the magnitude of uncertainties in future hydroclimatic conditions arising from natural variability over 25 years is larger than uncertainties arising from selection of emission scenarios used to generate the climate projections.

In this case study, we sampled 100 change factors from the UKCP09 change factor distribution, to derive s_f , $f = 1, \dots, 100$ possible future states of the climate. We use each of these change factors to condition w_o , $o = 1, \dots, 100$ runs of the stochastic weather generator, resulting in a total of 10,000 equally probable Monte Carlo samples of future rainfall and PET variables for the years 2015–2040. As in previous applications of this stochastic weather generator to the case study area [Borgomeo *et al.*, 2014], we have configured it to provide time series of weather variables spatially averaged for the Thames basin at Kingston. For more

Thames Water carried out scenario analysis to explore the robustness of the plans to significant future uncertainties [Thames Water, 2014]. The method proposed here goes significantly beyond this existing practice by explicitly quantifying probabilities of system failure and exploring trade-offs with financial costs of water resources management plans.

Municipal water users are supplied by surface reservoirs filled via direct pumping from the river Thames and by ground-

detailed information on the UKCP09 projections and their application in the Thames basin, the reader is referred to *Borgomeo et al.* [2014] and *Glenis et al.* [2015].

The precipitation and potential evapotranspiration sequences from the stochastic weather generator were run through CATCHMOD, a lumped rainfall-runoff model specifically designed for climate change studies [Wilby et al., 1994]. CATCHMOD has been widely used for water management purposes and climate change impact assessment studies in the Thames basin [Wilby and Harris, 2006; New et al., 2007; Manning et al., 2009; Borgomeo et al., 2014]. Daily river flows for the Thames at Kingston were simulated using the model parameterization recommended by Wilby [2005], to which the reader is referred to for more details on CATCHMOD's structure and parameter identifiability. CATCHMOD and the recommended parameters were chosen for illustrative purposes only, but other hydrological models and different parameterizations could be accommodated in our framework to explore the impacts of hydrological model uncertainty on the risk metric. We also note that CATCHMOD's parameters were calibrated on historical conditions and that some of these parameters may change depending on future land use and climate conditions. Although this approach is common to other applications of CATCHMOD in climate change studies [e.g., Wilby and Harris, 2006; New et al., 2007; Lopez et al., 2009; Wilby et al., 2011], future work should investigate how climate change may affect CATCHMOD's parameter values.

A simple water balance model was constructed to represent London's urban water supply system. Two nodes are used to represent domestic and environmental demands, and a storage node is used to represent the combined capacity of London's reservoirs. The single reservoir is simulated as being filled by direct abstraction from the Thames at Kingston. To estimate reservoir releases to the demand nodes, the model follows the rules in the Lower Thames Operating Agreement (Figure 2). Water is released to meet environmental water demands, which are a function of the capacity in the reservoir, and domestic water demands, which are subject to restrictions as specified in the Lower Thames Operating Agreement (Figure 2). Progressively more severe water use restrictions are imposed on domestic demand as storage capacity drops below each one of the four levels shown in Figure 2, resulting in the demand reductions shown in Table 1. Output from groundwater sources, accounting for 20% of total supplies, is assumed to be constant throughout the simulations and set to the maximum groundwater output during a drought defined by the water utility [Thames Water, 2014].

We used domestic water demand estimates from the water utility for 2015 [Thames Water, 2014] and considered demand to be independent of climatic conditions, an assumption which is justified by studies of the impacts of climate change on water consumption in the area [HR Wallingford, 2012]. A moderate population growth scenario (0.5% growth per annum from 2015 levels) is assumed for illustrative purposes. The water system model was run on a monthly time step to reduce computational requirements. Given that reservoir capacity in London buffers variability over weekly time scales and that drought in the Thames basin have a slow onset, a monthly time step is sufficient to capture the occurrence of water restrictions.

The streamflow ensemble generated using CATCHMOD was used as input to the water resource system model to simulate reservoir levels and estimate the annual frequency of water restrictions for each simulation and the probability of exceeding the target frequencies shown in Table 1.

3.3. Problem Formulation and Planning Alternatives

In this application, we seek to identify the trade-offs between financial costs of adaptation and the probability of exceeding the target frequency of different water use restrictions. To present results aligned with current water resources planning practices employed by the water utility in London, we adopted a 25 years planning horizon from 2015 to 2040 and only considered the planning options listed by the water utility as feasible in their 2014 water resources management plan [Thames Water, 2014]. The set of feasible planning options identified by the water utility and used in the optimization is shown in Table S1 in the supporting information. We note that these options and capital and operational costs were chosen for illustrative purposes only and that associated assumptions and uncertainties (e.g., future energy prices) were not explored in this study.

A total of 45 different planning options pertaining to five different groups were considered: (i) options to increase raw water abstractions and aquifer recharge, (ii) options to increase raw water imports, (iii) reuse and desalination options, (iv) new reservoir options, and (v) options to reduce distribution losses and

demands. The optimization was constrained to avoid the implementation of two options from the same group in the same plan (i.e., individual options within each group are considered mutually exclusive), with the exception of the options to increase raw water abstractions and aquifer recharge, whose implementation in the same plan was allowed following Thames Water's approach [Thames Water, 2014].

Instead of using a continuous decision variable for the *option's yields*, we adhered to the water utility's approach and used discrete values. We note that within our framework, options' yields or demand savings could be represented as continuous decision variables. Furthermore, we recognize that other nontraditional types of options such as operational decisions [e.g., Anghileri *et al.*, 2013] could be included as decision variables.

A decision variable corresponding to the time of implementation of each option was also included in the optimization. This decision variable specifies the year when the option starts to provide the expected benefit in terms of extra water supply or reduced water demand. In the case of the options to reduce distribution losses and demands, the total expected demand savings shown in Table S1 (supporting information) are equally distributed over a 20 year time window. For particular options (e.g., reservoirs), the time of implementation was constrained by the earliest potential start date specified in Table S1 (supporting information).

Five objectives were included in the optimization: minimization of the plan's financial costs and minimization of the probability of exceeding the target frequency for each one of the four levels of restrictions shown in Table 1 over the entire planning period (2015–2040). The costs for each option are shown in Table S1 (supporting information). Financial costs include the net present value of capital expenditures incurred to build each option and the expenditures associated with the option's operation, using a discount rate of 4.5% [Thames Water, 2014].

3.4. Multiobjective Optimization

There are two main multiobjective optimization approaches: classic and heuristic methods. Classical optimization methods, which have been applied in the last four decades, are typically based on mathematical programming approaches that under certain conditions ensure convergence to a *Pareto optimal solution* [Deb, 2001]; however, these methods convert the multiobjective optimization to a single-objective optimization problem to obtain one Pareto optimal solution at a time and have to be applied many times, with the aim of finding a different Pareto solution at each iteration [Deb *et al.*, 2002]. This can be inefficient compared with heuristic methods, such as evolutionary algorithms, whose search for solutions does not require single-objective optimization and which do not require full evaluation of the solution space, thus considerably reducing computational efforts. Evolutionary algorithms have proved to be able to successfully identify trade-offs amongst objectives in a range of water resources applications as described in Nicklow *et al.* [2010], Reed *et al.* [2013], and Maier *et al.* [2014] to which the reader is referred for more details on evolutionary algorithms and their specification for water resources problems.

To carry out the multiobjective optimization and discover risk-cost trade-offs, we employ the ϵ -dominance multiobjective optimization evolutionary algorithm (ϵ MOEA). ϵ MOEA has been successfully applied to solve multiobjective water resources problems [Mortazavi-Naeini *et al.*, 2014, 2015a, 2015b]. ϵ MOEA is a member of the evolutionary algorithm family whose distinguishing feature is the use of the ϵ -dominance concept, which divides the objective space into hyperboxes of size ϵ and allows only one nondominated solution to reside in each box [Laumanns *et al.*, 2002]. Inclusion of this concept in an evolutionary algorithm produces a method capable of maintaining a diverse and well-distributed set of solutions with a small algorithmic computational cost. Another advantage of applying the ϵ -dominance concept is that it ensures that there are no solutions within an ϵ_i from each other in the i th objective. This makes the method highly practical as decision-makers can adjust closeness of the solutions on the Pareto frontier by changing the ϵ value of each objective [Deb *et al.*, 2003].

ϵ MOEA solutions are formed from two coevolving populations including the population of parents, noted $P()$, and the population of ϵ -dominance archived solutions, noted $E()$. In ϵ MOEA, as in other evolutionary algorithms, candidate solutions are represented as an array of bits (e.g., binary strings of 0 and 1 s). The ϵ MOEA begins with an initial population $P(0)$. The ϵ -dominance solutions of $P(0)$ form the initial archived population $E(0)$. At generation t , the optimizer chooses two parents, one each from population. By applying genetic operations such as crossover, mutation, and inversion on parents, an offspring is produced and

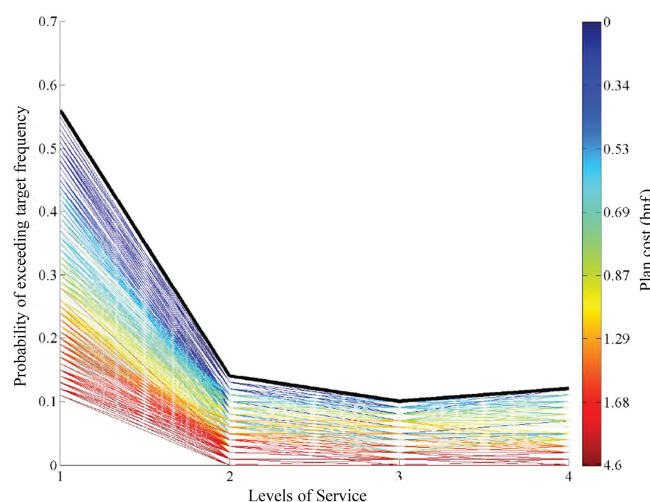


Figure 3. Parallel coordinates plot of the epsilon-nondominated Pareto optimal set. Each solution (a 25 years plan) is represented by a line, with the color of each line representing the financial cost of the plan (color bar on the right-hand side). The vertical position of the line vertices represents the probability of exceeding the target frequency value of the corresponding Levels of Service, listed on the horizontal axis. The black line indicates the current system performance.

consequently its associated objective values are assessed. Crossover is the partial exchange of bits between two parents. Mutation changes a random bit of a parent to its reverse value, i.e., from 0 to 1 or 1 to 0. In fact, mutation helps to prevent converging to a local optimum. An inversion operator is applied independently after crossover and mutation. Under the inversion, two randomly selected bits are swapped.

For a candidate solution to be included in the population, three possibilities exists: (i) if the new solution dominates any existing nondominated solutions, it replaces one at random; (ii) if it is dominated by any existing nondominated solutions, it is rejected; (iii) if it is nondominated with respect to the existing nondominated solutions, it replaces a random member of the

population. For its inclusion in the archive, there are also three possibilities: (i) if the new solution is not ϵ -dominated by any solutions in the archive; (ii) if it ϵ -dominates any member of the design, it randomly replaces a dominated design; (iii) if the new design is ϵ -nondominated, and if it does not occur in any other solution.

Based on previous applications of ϵ MOEA to water resources optimization studies [Mortazavi *et al.*, 2012; Mortazavi-Naeini *et al.*, 2014, 2015a, 2015b], we set the following ϵ MOEA parameters: (i) probability of crossover = 1, (ii) probability of mutation = 0.01, and (iii) probability of inversion = 0.005. The maximum number of iterations was set to 10,000. The ϵ MOEA epsilon values were set to 1000 for the first objective (financial cost minimization) and 0.0026 for the other objectives to be sufficiently small to ensure high resolution. The termination condition was defined as either reaching the maximum number of iterations or no changes in the Pareto frontier for 500 iterations. The multiobjective optimization was performed using a i5 Intel Core machine with a 3.4 GHz processor on a 64 bit operating system. This resulted in approximately 36 h of model evaluations for 10,000 iterations.

4. Results

4.1. Multiobjective Cost and Risk Reduction Trade-Offs

The Pareto optimal solutions identified in the multiobjective optimization are shown in the parallel coordinates plot in Figure 3. The Pareto optimal solutions are the solutions to the optimization problem in which further improvement in one objective cannot be made without sacrificing performance in other objectives. Thus, our results illustrate trade-offs between performance at four Levels of Service and total discounted financial costs. In Figure 3, the x axis shows the four objectives related to the probability of exceeding the target frequency of each Level of Service and the colors represent the cost objective. The performance of each solution (i.e., a 25 years water resources management plan) is represented as a line crossing the four objectives colored according to the plan's financial costs. The current system's performance with respect to the four risk objectives is shown with a solid black line.

The parallel coordinates plot shows that in the current system (solid black line in Figure 3), the probabilities of exceeding the target frequencies of water restrictions over the 2015–2040 planning period are of the order of 0.1–0.15 for Levels of Service 2–4 and of the order of 0.55 for Level 1. The optimizer is capable of finding solutions that minimize to near zero the probability of exceeding the target frequencies for restriction Levels 2, 3, and 4. As expected, the minimization of these three objectives comes at an increasing financial cost. The absence of solutions with a probability of less than 0.1 of exceeding the target frequency of a

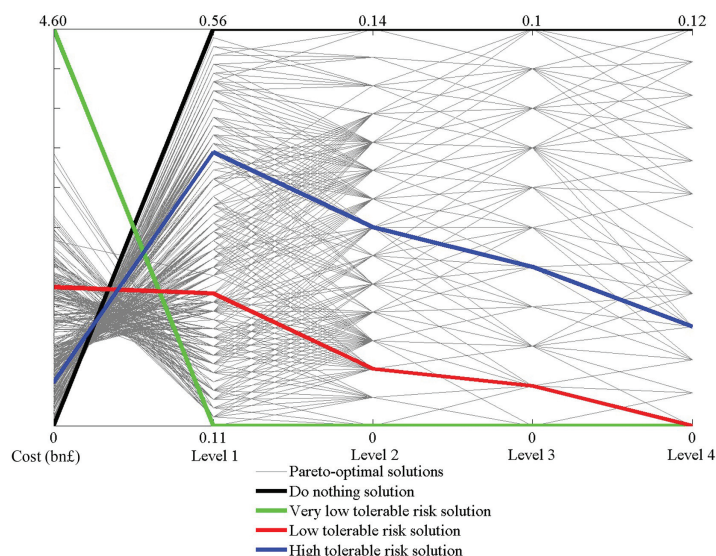


Figure 4. Parallel coordinates plot of the epsilon-nondominated Pareto optimal set. Each solution (a 25 years plan) is represented by a line. The vertical position of the line vertices represents the relative value of the solution's objective function. The objective function values for financial cost and the probabilities of exceeding the four Levels of Service are shown. Note that the objectives' values are normalized between their maximum and minimum values and that the direction of preference (minimization) is always downward.

and minimum values [cf. *Giuliani et al.*, 2014]. As in Figure 3, the solid black line shows the objectives obtained with the system in its current state.

On one hand, Figure 4 shows that significant trade-offs exist between the financial cost of the water resources management plans and their ability to reduce the probability of exceeding the target frequency of water restrictions. On the other hand, the lack of line crossings between Levels 2, 3, and 4 suggests that there is little trade-off between these objectives: reducing the probability of exceeding a Level 2 and 3 restriction also reduces the probability of exceeding a Level 4 restriction at no additional cost. For the Level 1 restrictions, some of the solutions indicate some trade-offs, suggesting that reducing the probability of exceeding the target frequency for a Level 1 restriction may come at a significant extra cost which does not necessarily reduce the probabilities of exceeding the targets for the other three levels of restriction.

To show how our approach can be used to understand the implications of different risk attitudes on the selection of the optimal plan, we highlight three solutions in Figure 4. The green line shows a solution that would be preferred by an extremely risk-averse decision-maker, whose primary objective is to minimize risk across the four levels of restriction irrespective of the financial costs. A decision-maker with a low but more refined tolerable risk profile may select the plan highlighted in red, where little attention is paid to minimizing the probability of exceeding the target frequency of a Level 1 restriction and where the primary objective is to minimize the probability of exceeding the target frequency for the high impact Levels 3 and 4 restrictions. This tolerable risk profile would result in a significantly lower financial cost than the plan highlighted in green. A third decision-maker with high risk tolerability may select the solution highlighted in blue.

Table 2 provides a summary of the water resources management plans labeled in Figure 4. The table shows how, irrespective of the risk tolerability, two aquifer recharge options to increase raw water abstractions are never found in the plans presented in Figure 4 because of their high operational costs (see Table S1 in the supporting information). Reuse and desalination options were implemented in all three highlighted water resources management plans, with higher capacity options being favored to achieve lower tolerable risk. Water transfer options were implemented in the high and low tolerable risk solutions. For very low tolerable risk, the optimizer opts for a reservoir and a demand management option instead of a water transfer option. This is due to the very large capital expenditures associated with high-capacity water transfers.

Level 1 water restriction indicates that this target is much more difficult to attain. This may be due to the fact that the optimizer is constrained to implement major supply-side options later in the planning period (because of the associated lead time) and that the benefits of demand management interventions accrue over a long period of time, leading to Level 1 restrictions occurring early on.

To examine more closely the cost-risk reduction trade-offs, Figure 4 shows another parallel coordinates plot for the same set of solutions, with an additional axis for financial cost. In Figure 4, the objective values for all five objectives have been normalized to their maximum

Table 2. Characteristics of the Three Solutions Highlighted in Figure 4^a

Risk Tolerability	Cost (k£)	Level Level Level Level				GW Enhancement	Aquifer Storage and Recovery	AR SLARS	AR Kidbrooke	AR Hornsey	AR Streatham	AR Merton	AR Kidbrooke	Transfer	Reuse	Reservoir	Demand Management
		1	2	3	4												
High	500,430	0.42	0.07	0.04	0.03	2039	0	0	2026	2024	2033	2033	2017	Oxford Canal in 2028	IPR Deephams STW 60 Mld in 2036	0	0
Low	1,604,974	0.26	0.02	0.01	0	2030	0	0	2024	2031	0	2020	0	RWT 75 ML/d in 2038	IPR Abbey Mills 150 ML/d in 2022	0	0
Very Low	4,601,232	0.11	0	0	0	2018	0	0	2035	2032	2017	2033	0	0	IPR Becton STW 100 ML/d in 2034	RES Abingdon 179 ML/d LON 105-0 in 2017	75 in 2027

^aRefer to Table S1 (supporting information) for the estimated capacities of the options. AR: Artificial Recharge, RWT: Raw Water Transfer, IPR: Indirect Potable Reuse, and STW: Sewage Treatment Works.

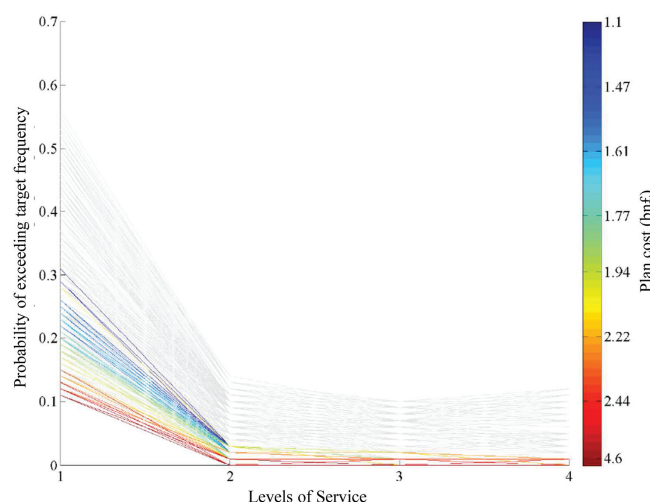


Figure 5. Parallel coordinates plot subject to risk tolerability constraint, showing in grey the solutions that have a probability of exceeding the Level 4 target frequency greater than 0.01. Color is used to show the financial cost of the solutions that satisfy the constraint.

4.2. Filtering Solutions Subject to Tolerable Risk Constraints

In practice, the full set of Pareto optimal solutions displayed in Figure 3 may not be of interest to decision-makers because some solutions may have risk profiles higher than the water utility's minimum performance requirements in terms of probabilities of exceeding the target frequency of water restrictions. Water managers in London define the Level 4 water restriction as the most important criteria for comparing decisions and evaluating plans. This is because a Level 4 water restriction would have disastrous consequences on London's socioeconomic activities. The implications of tolerable risk choices around this important system performance criteria can be explored by

“brushing” the optimal solutions set [cf. Kasprzyk *et al.*, 2013], that is, by only focusing on solutions that have a 0.01 or lower probability of exceeding the target for a Level 4 restriction (Figure 5). This implies that water managers accept a 0.01 probability of having to impose a severe water use restriction with a frequency greater than 0.005 per year.

The solutions shown in Figure 5 have similar performance in terms of the Level 2 and Level 3 objectives, so a decision-maker seeking to minimize cost subject to the Level 4 tolerable risk constraint may select the least cost water resources management plan from this set. A more risk-averse decision-maker may select the least cost solution capable of reducing the probability of exceeding the target frequency of a Level 4 restriction to zero.

4.3. Evaluating Relationships Between Decisions and Objectives

We now examine the properties of the Pareto optimal plans to determine which options occur more frequently and how the type of options selected by the optimizer relates to the probability of exceeding the target frequency of a Level 4 restriction. Figure 6 shows four scatter plots, one for each type of option in Table S1 (supporting information). We focus here on the major (in terms of projected yield or demand reduction) types of options including water transfer, reuse and desalination, reservoir and leakage reduction and demand management options. For each of the four types of planning options, we plotted the probability of exceeding the target frequency of a Level 4 water restriction against the time of implementation of different options. The size of the markers in Figure 6 is proportional to the number of Pareto optimal solutions with a particular combination of objective value and year of implementation.

For each type of option, the optimizer tends to select just a few options. Observe this in Figure 6b, which shows that just six out of a total of 14 possible reuse and desalination options have been implemented by the optimizer. A similar observation can be made for the other types of options. This is due to the tendency of the optimizer to implement options whose financial costs are lower for a given option capacity. Desalination plants have an output capacity equal to the reuse options; however, they are not implemented by the optimizer because of their higher operational costs.

Among the transfer options (Figure 6a), the optimizer selects the 17 ML/d Oxford canal transfer option for probabilities of exceeding the target frequency of a Level 4 restriction greater than 0.01. When the value of this objective tends to zero, the optimizer selects the higher 75 ML/d capacity transfer, which is implemented in most plans after 2035. A similar relationship between the options selected for different levels of risk can be observed in Figure 6b for the reuse options. The 60 ML/d option is preferred only for probability levels greater than 0.02. To reduce risk below a 0.02 probability of exceeding the target, it becomes clear

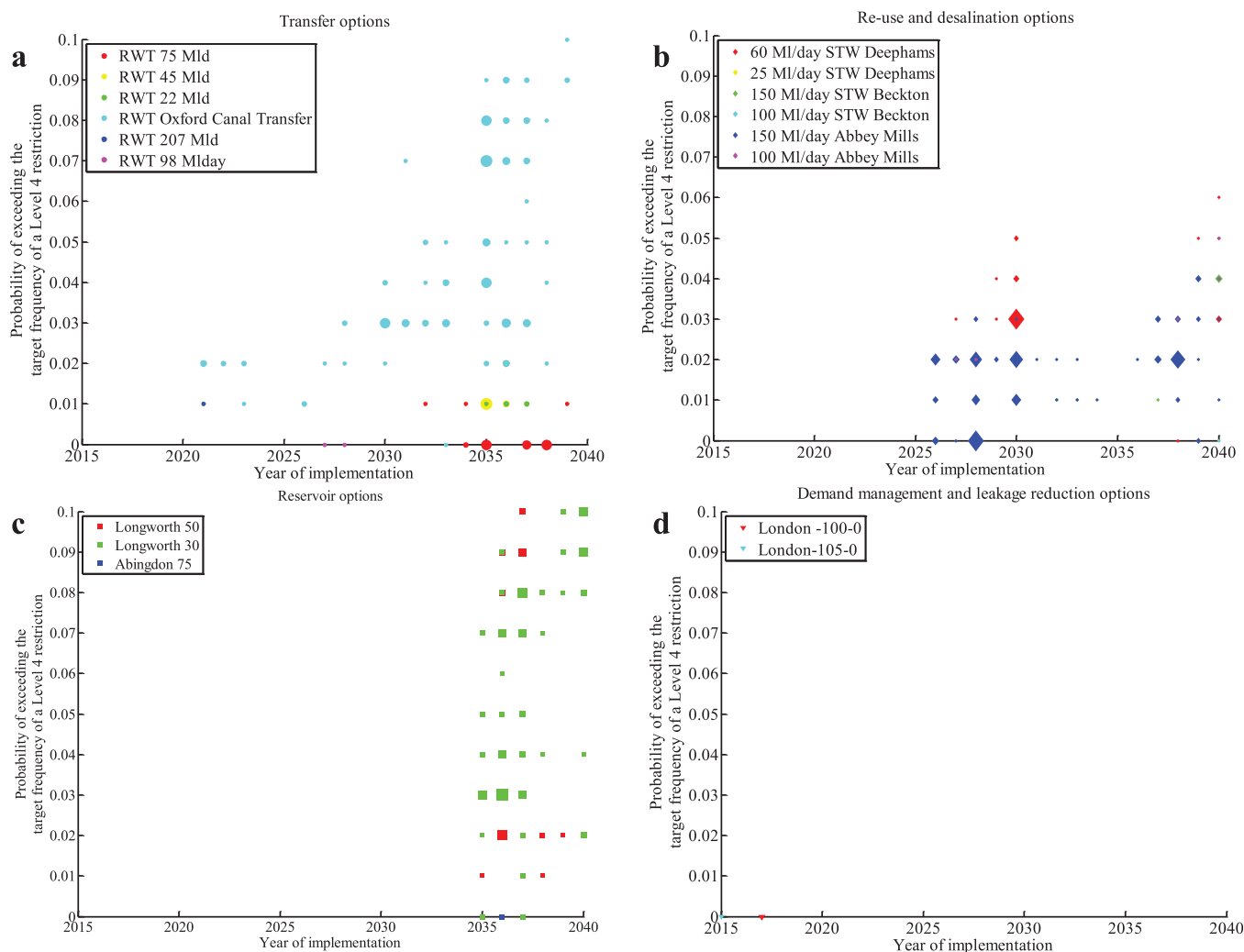


Figure 6. Scatterplots of (a) transfer, (b) reuse and desalination, (c) reservoir, and (d) demand options implemented by the optimizer for different probabilities of exceeding the target frequency of a Level 4 restriction and years of implementation. See Table 2 for full definition of these options.

that water managers would need to implement a more expensive reuse facility with greater capacity (blue diamonds in Figure 6b) soon after 2025.

The optimizer's selection of reservoir decisions is not as dependent on the value of the risk reduction objective (Figure 6c), as the optimizer does not prefer a particular reservoir option for a particular level of risk. The Longworth 30 reservoir is the preferred option, due to its lower financial costs, for higher risk tolerability. For risk tolerability lower than 0.03, the larger Longworth 50 reservoir is the preferred option. All reservoirs options across the Pareto optimal set are implemented after 2035, indicating that choice around this type of planning option could be delayed to the 2020s.

Leakage reduction and demand management strategies are present only in a few solutions and are implemented early on in the planning period (bottom left in Figure 6d). This effect can be ascribed to the large operating costs of leakage reduction and demand management strategies, which prevent the optimizer from implementing them. We note that the options implemented by the optimizer reflect the costing and the objectives specified in the optimization problem formulation, which were taken from the water utility's water management plan [Thames Water, 2014]. Different results may be obtained by employing different costing methodologies and by specifying different objectives (i.e., environmental costs) or constraints.

To further explore the relationship between the five objectives and the plans which satisfy the Level 4 tolerable risk constraint, we plot each plan according to the options implemented and the year of implementation

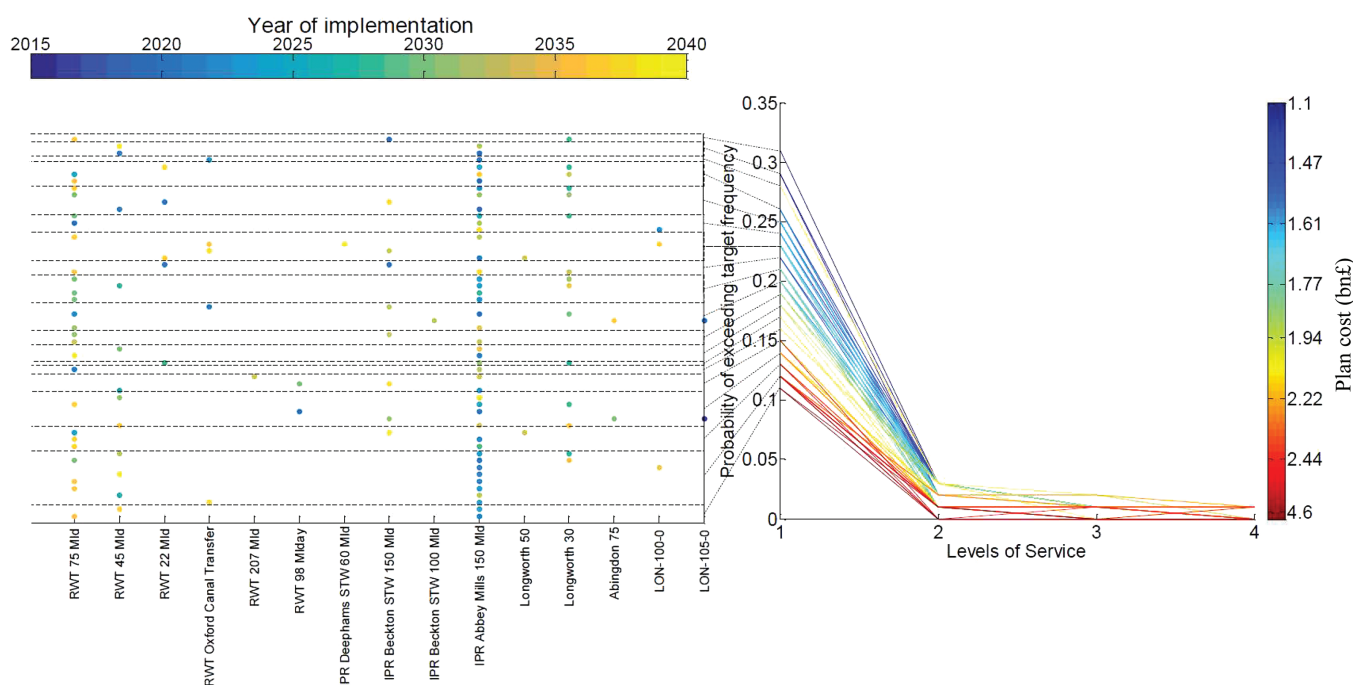


Figure 7. Relationship between objectives, options, and year of implementation for solutions with a probability of exceeding the Level 4 target frequency lower than or equal to 0.01. See Table S1 (supporting information) for a full definition of these options.

(left-hand side of Figure 7) and juxtapose it to the parallel coordinate plot (right-hand side of Figure 7) showing the plans' performance with respect to the five objectives. This allows us to simultaneously visualize the combination of options in each plan and the corresponding values of the objectives. The color bar on the right-hand side refers to the financial cost of each plan.

Each point in the left-hand side represents a particular option. The horizontal position of the points indicates the type of option, listed on the horizontal axis. The vertical position of the points represents the Level 1 objective value, which can be read by following the connecting lines to the plot on the right-hand side. The color of the point indicates the year of implementation of that option according to the color bar in the top-left of Figure 7. Each single row in the left-hand side represents a water resources management plan (i.e., a specific combination of options). Rows with the same value of the Level 1 objective are enclosed in the same box (dotted lines) in the left-hand side. The lines from the right-hand side plot are connected to the center of the boxes in the left-hand side which contain the plans with the same value for the Level 1 objective.

Figure 7 can be used to visualize objectives and type of options at the same time. It shows that the majority of solutions satisfying the tolerable risk constraint contain the Indirect Potable Reuse 150 ML/d option. The Indirect Potable Reuse Abbey Mills option is the most constantly favored option in the plans which satisfy the constraint (i.e., Level 4 risk less than or equal to 0.01) because this option provides the most capacity for the least financial costs and it is therefore preferred by the optimizer. No clear relationship between the types of options emerges, that is, no two options always occur together or exclude each other.

5. Discussion and Conclusions

Achieving secure water supplies in the context of a changing climate and increasing human demands for water will involve exploration of trade-offs between risk and financial cost of alternative water resources management plans. Identifying robust sequences of supply and demand-side investments will involve extensive option searching, system performance appraisal, and robustness analysis. In this paper, we have

presented methods, together with an illustrative case study, for evaluating alternative water resource management plans in terms of probabilities of exceeding the target frequency of water restrictions and financial costs. Failure of water resources systems can result in consequences of varying levels of impact, from relatively minor inconvenience to major economic disruptions and environmental impacts. Evaluation of adaptation options therefore needs to consider a range of different severities of system failure and associated consequences. In this study, we have explicitly evaluated the probability of exceeding the tolerable frequency of four different levels of severity of water restrictions. Those tolerable frequencies have previously been determined through deliberation within the water utility, economic appraisal, and willingness-to-pay surveys with customers. We have identified which levels of water restrictions have most influence on the financial costs of adaptation. In the case study, we have demonstrated that it is not possible to achieve the same probability of exceedance with respect to all four risk criteria, suggesting that these criteria are not well balanced and may be in need of review. This explicit representation of trade-offs can be used to stimulate reflection about tolerable risk. A least-cost constrained optimization approach would have given unnecessary emphasis on minimizing the probability of exceeding the target frequency for the low severity and low impact Level 1 restriction, at excessive financial cost.

All of society and the environment would be impacted by severe water restrictions, so identification of tolerable levels of risk and proportionate adaptation requires careful deliberation amongst a range of stakeholders. Thresholds of tolerable risk can be expected to change, for example, during and following a major drought [Stakhiv, 2011]. By explicitly presenting plan performance in terms of risks of observable outcomes of interest to water users (i.e., water use restrictions), our approach could inform these wider societal discussions around water-related tolerable risk.

In this study, we have adopted financial cost estimates from the water utility for illustrative purposes. Sensitivity to uncertainty in cost estimates, for example, associated with demand management options, should be explored. Future work will explore the sensitivity of the optimal solutions to discount rates [e.g., Mortazavi-Naeini *et al.*, 2014]. In this study, options are implemented as a deterministic sequence in each 25 years water resources management plan. This approach could be extended to the appraisal of strategies in which optionality (e.g., possibility to defer, expand, or abandon between options) is included as a decision variable [e.g., Jeuland and Whittington, 2014]. Furthermore, we recognize that each of the decisions has associated environmental impacts, which we did not seek to quantify in this study. Environmental impacts, either monetized or as other indicators such as flow alterations or environmental flow deficits (or benefits) [e.g., Erfani *et al.*, 2015], could be included as objectives in our optimization framework, and future work will seek to understand how including environmental considerations affects the optimizer search for Pareto optimal solution [e.g., Hurford and Harou, 2014].

The focus of this paper is on selecting decisions based on current operational policies and risk attitudes. We recognize that these policies and preferences may change in the future in response to a changing water system and climate [Wade *et al.*, 2013]. Capturing the feedbacks between hydrological change, represented in our model, and social changes and preferences would require a considerable extension of our simulation framework and could be the subject of future human-hydrology system modeling studies [e.g., O'Connell and O'Donnell, 2014; Di Baldassarre *et al.*, 2015]. In the case study, we assume that reservoir triggers will remain constant after the implementation of supply-side or demand-side options. Although evidence from the water utility suggests that the reservoir triggers will not be changed in the next rounds of water resources management planning, this assumption will be tested in the future with a water system simulator capable of incorporating changes in operating policies within the longer-term water resources management plan simulation.

The case study's hydrological and water system modeling framework is subject to several limitations and assumptions. Although the CATCHMOD parameter set used in this study was shown to reproduce well-observed data for the Thames at Kingston [Wilby, 2005; Borgomeo *et al.*, 2014], previous research suggests that uncertainty in flow projections due to parameter equifinality can be significant, especially for projections of low flows. Furthermore, CATCHMOD's parameters are kept constant throughout the simulation, implying that changes in land use and catchment response are ignored. Similarly, changes in groundwater output and storage were not modeled. These assumptions are justified given our study's focus on trade-offs between risk metrics and financial costs of water resources management plans, but future work should

investigate the impact of hydrological model parameter uncertainty on the case study's results and employ a water model capable of resolving groundwater storage and abstraction.

As emphasized elsewhere [Borgomeo *et al.*, 2014; Hall and Borgomeo, 2013], we are aware of the limitations of using climate model projections to estimate the occurrence of future events. Our approach is based on extensive sampling of hydrological variability, conditioned upon climate model projections from a very large ensemble of GCM runs. In all, this has amounted to each plan being subject to some ten thousands different flow series, which span a very wide range of future nonstationary climatic conditions. The objective function is based on a relatively small proportion of these simulations resulting in system failures, so in that sense it can be regarded as a robust methodology. To further investigate the robustness of selected plans to residual uncertainties or hydroclimatic changes which are not well represented by climate model projections (i.e., changes in persistence [Rocheta *et al.*, 2014]), the trade-off analysis presented here could be coupled with vulnerability-based and robustness analysis [e.g., Nazemi *et al.*, 2013; Herman *et al.*, 2014; Borgomeo *et al.*, 2015b].

The multiobjective optimization approach proposed in this study requires water managers to carry out extensive simulation studies. The small extra costs associated with running multiple simulations will be justified because of the high capital costs associated with adaptation decisions that water utilities around the world will be facing in the next decades. The computational requirements could be easily overcome with parallel computing.

Our results suggest that under a moderate population growth scenario (0.5% growth per annum), the London water supply system would require a reuse supply-side option in the mid-2020s to satisfy the tolerable risk constraint expressed by the water utility in the area. More significant demand or supply-side options, including reservoirs and transfers, may be required in the mid-2030s. Alternative options, beyond those considered here, that derive from the water resources management plan, could readily be added to the option set. It should be stressed that the analysis is based on a simplified representation of Thames Water's system and that the results should be further tested with the full system model which implements more complex operational rules.

Appendix A

Option. An investment or intervention that may provide additional water supply or reduce water demand.

Option Yield. Volume of water that can be supplied by a proposed investment in water supply infrastructure.

Water Resources Management Plan (Also Referred to as Plan). A specific combination and scheduling of options over 25 years.

Financial Cost (Also Referred to as Cost). Total present value of capital and operational expenses in GBP associated with each option.

Target Frequency of Water Restrictions. Maximum annual frequency with which a water utility will impose restrictions on water users. This is called Level of Service in the UK.

Risk. In general, the combination of the probability of an event and its negative consequences [UNISDR, 2009]. Here the negative consequences are associated with restrictions, of different levels of severity, on water use. Therefore, in this context, risk is the probability of exceeding a target frequency of water restrictions of given severity.

Tolerable Risk. Level of risk (as defined above) that the water utility plans for given the willingness of water users to pay to obtain a further incremental reduction in risk.

Risk Attitude. Water manager's preferences in terms of tolerable risk.

Risk-Based Decision-Making. Comparing alternative water resources management plans based on their ability to reduce the probability of occurrence/exceedance of water restrictions of given severity and their financial costs.

Robustness Analysis. The analytical process of subjecting water resources management plans to a wide range of possible future states of the world in order to evaluate their performance and identify robust plans.

Robust Plan. A water resource management plan that performs acceptably across a wide range of possible future states of the world.

Pareto Optimal Solutions. Solutions whose performance in one objective cannot be improved without degrading performance in some other objective.

Climate Projection. Climate-model-derived time series of future climate variables (e.g., precipitation and temperature).

Trade-Offs. Situation where achieving a positive outcome in one water planning objective involves a deterioration in another objective.

Acknowledgments

Edoardo Borgomeo is funded by the Engineering and Physical Sciences Research Council, the Environment Agency (science project SC120053), and Thames Water. This work was partially supported by the Natural Environment Research Council (MaRIUS: Managing the Risks, Impacts and Uncertainties of droughts and water Scarcity, NE/L010364/1). We would like to thank Howard Wheeler and Simon Dadson for comments on an earlier version of this manuscript. The streamflow data used in this paper are available from the National River Flow Archive—Centre for Ecology and Hydrology database. Data set name: 39001—Thames at Kingston (<http://www.ceh.ac.uk/data/nrfa/data/station.html?39001>). The water resource system data can be found in *Thames Water* [2014]. The climate projection and hydrological model can be obtained from the corresponding author. We thank the Associate Editor and three anonymous reviewers whose comments and suggestions greatly improved the paper.

References

- Anghileri, D., A. Castelletti, F. Pianosi, R. Soncini-Sessa, and E. Weber (2013), Optimizing watershed management by coordinated operation of storing facilities, *J. Water Resour. Plann. Manage.*, 139(5), 492–500.
- Beh, E. H. Y., G. C. Dandy, H. R. Maier, and F. L. Paton (2014), Optimal sequencing of water supply options at the regional scale incorporating alternative water supply sources and multiple objectives, *Environ. Modell. Software*, 53, 137–153.
- Beh, E. H. Y., H. R. Maier, and G. C. Dandy (2015), Adaptive, multiobjective optimal sequencing approach for urban water supply augmentation under deep uncertainty, *Water Resour. Res.*, 51, 1529–1551, doi:10.1002/2014WR016254.
- Ben-Haim, Y. (2006), *Info-Gap Decision Theory: Decisions Under Severe Uncertainty*, 2nd ed., Academic, London, U. K.
- Borgomeo, E., J. W. Hall, F. Fung, G. Watts, K. Colquhoun, and C. Lambert (2014), Risk-based water resources planning: Incorporating probabilistic nonstationary climate uncertainties, *Water Resour. Res.*, 50, 6850–6873, doi:10.1002/2014WR015558.
- Borgomeo, E., C. L. Farmer, and J. W. Hall (2015a), Numerical Rivers: A synthetic streamflow generator for water resources vulnerability assessment, *Water Resour. Res.*, 51, 5382–5405, doi:10.1002/2014WR016827.
- Borgomeo, E., G. Pflug, J. W. Hall, and S. Hochrainer-Stigler (2015b), Assessing water resource system vulnerability to unprecedented hydrological drought using copulas to characterize drought duration and deficit, *Water Resour. Res.*, 51, 8927–8948, doi:10.1002/2015WR017324.
- Braga, B. P. F., J. G. L. Conejo, L. Becker, and W. W. G. Yeh (1985), Capacity expansion of Sao-Paulo water-supply, *J. Water Resour. Plann. Manage. Div. Am. Soc. Civ. Eng.*, 111(2), 238–252.
- Brown, C., and R. L. Wilby, (2012), An alternate approach to assessing climate risks, *Eos Trans. AGU*, 93(41), 401–402.
- Brown, C., W. Werick, W. Leger, and D. Fay (2011), A decision-analytic approach to managing climate risks: Application to the Upper Great Lakes, *J. Am. Water Resour. Assoc.*, 47, 524–534, doi:10.1111/j.1752-1688.2011.00552.x.
- Brown, C., Y. Ghile, M. Lavery, and K. Li (2012), Decision scaling: Linking bottom-up vulnerability analysis with climate projections in the water sector, *Water Resour. Res.*, 48, W09537, doi:10.1029/2011WR011212.
- Brown, C. M., J. R. Lund, X. Cai, P. M. Reed, E. A. Zagana, A. Ostfeld, J. Hall, G. W. Characklis, W. Yu, and L. Brekke (2015), The future of water resources systems analysis: Toward a scientific framework for sustainable water management, *Water Resour. Res.*, 51, 6110–6124, doi:10.1002/2015WR017114.
- Burton, A., H. J. Fowler, S. Blenkinsop, and C. G. Kilsby (2010), Downscaling transient climate change using a Neyman-Scott Rectangular Pulses stochastic rainfall model, *J. Hydrol.*, 381(1–2), 18–32, doi:10.1016/j.jhydrol.2009.10.031.
- Dandy, G. C., and M. Engelhardt (2006), Multi-objective trade-offs between cost and reliability in the replacement of water mains, *J. Water Resour. Plann. Manage.*, 132(2), 79–88.
- Deb, K. (2001), *Multi-Objective Optimization Using Evolutionary Algorithms*, John Wiley, Chichester, U. K.
- Deb, K., A. Pratap, S. Agarwal, and T. Meyarivan (2002), A fast and elitist multiobjective genetic algorithm: NSGA-II, *IEEE Trans. Evol. Comput.*, 6(2), 182–197.
- Deb, K., M. Mohan, and S. Mishra (2003), A fast multiobjective evolutionary algorithm for finding well spread pareto optimal solutions, *KanGAL rep. 2003002*, Indian Inst. of Technol., Kanpur, India.
- Diaz-Nieto, J., and R. Wilby (2005) A comparison of statistical downscaling and climate change factor methods: Impacts on low flows in the River Thames, United Kingdom, *Clim. Change*, 69(2–3), 245–268.
- Di Baldassarre, G., A. Viglione, G. Carr, L. Kuil, K. Yan, L. Brandimarte, and G. Blöschl (2015), Debates—Perspectives on socio-hydrology: Capturing feedbacks between physical and social processes, *Water Resour. Res.*, 51, 4770–4781, doi:10.1002/2014WR016416.
- Environment Agency (2013), *Water Stressed Areas—Final Classification*, Environ. Agency, Bristol, U. K.
- Erfani, T., O. Binions, and J. J. Harou (2015), Protecting environmental flows through enhanced water licensing and water markets, *Hydrol. Earth Syst. Sci.*, 19, 675–689.
- European Environment Agency (2007), Climate change and water adaptation issues, *EEA Tech. Rep. 2/2007*, Copenhagen.
- Giuliani, M., J. D. Herman, A. Castelletti, and P. Reed (2014), Many-objective reservoir policy identification and refinement to reduce policy inertia and myopia in water management, *Water Resour. Res.*, 50, 3355–3377, doi:10.1002/2013WR014700.
- Giuliani, M., A. Castelletti, F. Pianosi, E. Mason, and P. Reed (2015), Curses, tradeoffs, and scalable management: Advancing evolutionary multiobjective direct policy search to improve water reservoir operations, *J. Water Resour. Plann. Manage.*, 04015050, doi:10.1061/(ASCE)WR.1943-5452.0000570.
- Glenis, V., V. Pinamonti, J. W. Hall, and C. Kilsby (2015), A transient stochastic weather generator incorporating climate model uncertainty, *Adv. Water Resour.*, 85, 14–26, doi:10.1016/j.advwatres.2015.08.002.
- Groves, D. G., and R. J. Lempert (2007), A new analytic method for finding policy-relevant scenarios, *Global Environ. Change*, 17, 73–85.
- Hall, J. W. (2007), Probabilistic climate scenarios may misrepresent uncertainty and lead to bad adaptation decisions, *Hydrol. Processes*, 21(8), 1127–1129.
- Hall, J. W., and E. Borgomeo (2013), Risk-based principles for managing and defining water security, *Philos. Trans. R. Soc. A*, 371, 20120407.
- Hall, J. W., A. Brown, R. J. Nicholls, N. Pidgeon, and R. Watson (2012a), Proportionate adaptation, *Nat. Clim. Change*, 2(12), 833–834.
- Hall, J. W., G. Watts, M. Keil, L. de Vial, R. Street, K. Conlan, P. E. O’Connell, K. J. Beven, and C. G. Kilsby (2012b), Towards risk-based water resources planning in England and Wales under a changing climate, *Water Environ. J.*, 26, 118–129, doi:10.1111/j.1747-6593.2011.00271.x.

- Harou, J. J., M. Pulido-Velazquez, D. E. Rosenberg, J. Medellín, J. R. Lund, and R. E. Howitt (2009), Hydro-economic models: Concepts, design, applications, and future directions, *J. Hydrol.*, *375*, 627–643, doi:10.1016/j.jhydrol.2009.06.037.
- Hashimoto, T., J. R. Stedinger, and D. P. Loucks (1982), Reliability, resiliency, and vulnerability criteria for water resource system performance evaluation, *Water Resour. Res.*, *18*(1), 14–20, doi:10.1029/WR018i001p00014.
- Hensher, D., N. Shore, and K. Train (2006), Water supply security and willingness to pay to avoid drought restrictions, *Econ. Rec.*, *82*, 56–66.
- Herman, J., P. Reed, H. Zeff, and G. Characklis (2015), How should robustness be defined for water systems planning under change?, *J. Water Resour. Plann. Manage.*, 04015012, doi:10.1061/(ASCE)WR.1943-5452.0000509.
- Herman, J. D., H. B. Zeff, P. M. Reed, and G. W. Characklis (2014), Beyond optimality: Multistakeholder robustness tradeoffs for regional water portfolio planning under deep uncertainty, *Water Resour. Res.*, *50*, 7692–7713, doi:10.1002/2014WR015338.
- Horridge, M., J. Madden, and G. Wittwer (2005), The impact of the 2002–2003 drought on Australia, *J. Policy Model.*, *27*, 285–308.
- HR Wallingford (2012), Thames Water climate change impacts on demand for the 2030s, *Rep. EX6828*, Wallingford, U. K.
- Hughes, G., P. Chinowsky, and K. Strzepek (2010), The costs of adaptation to climate change for water infrastructure in OECD countries, *Utilities Policy*, *18*(3), 142–153.
- Hurford, A. P., and J. J. Harou (2014), Balancing ecosystem services with energy and food security—Assessing trade-offs from reservoir operation and irrigation investments in Kenya's Tana Basin, *Hydrol. Earth Syst. Sci.*, *18*, 3259–3277.
- Hurford, A. P., I. Huskova, and J. J. Harou (2014), Using many-objective trade-off analysis to help dams promote economic development, protect the poor and enhance ecological health, *Environ. Sci. Policy*, *38*, 72–86, doi:10.1016/j.envsci.2013.10.003.
- IPCC (2014a), Summary for policymakers, in *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by C. B. Field et al., pp. 1–32, Cambridge Univ. Press, Cambridge, U. K.
- IPCC (2014b), *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by Core Writing Team, R. K. Pachauri, and L. A. Meyer, 151 pp., Geneva, Switzerland.
- Jeuland, M., and D. Whittington (2014), Water resources planning under climate change: Assessing the robustness of real options for the Blue Nile, *Water Resour. Res.*, *50*, 2086–2107, doi:10.1002/2013WR013705.
- Kasprzyk, J., S. Nataraj, P. Reed, and R. Lempert (2013), Many objective robust decision making for complex environmental systems undergoing change, *Environ. Modell. Software*, *42*, 55–71.
- Kasprzyk, J. R., P. M. Reed, B. R. Kirsch, and G. W. Characklis (2009), Managing population and drought risks using many-objective water portfolio planning under uncertainty, *Water Resour. Res.*, *45*, W12401, doi:10.1029/2009WR008121.
- Korteling, B., S. Dessai, and Z. Kapelan (2013), Using information-gap decision theory for water resources planning under severe uncertainty, *Water Resour. Manage.*, *27*(4), 1149–1172, doi:10.1007/s11269-012-0164-4.
- Lambert, C. (2015), *Long term investment planning: Why is it needed? A Water company perspective, paper presented at the ForUM Workshop 2: Long term investment planning*, Univ. of Oxford, Oxford, U. K., 5 May. [Available at <http://www.eci.ox.ac.uk/research/water/forum/w2-lambert.pdf>].
- Laumanns, M., L. Thiele, K. Deb, and E. Zitzler (2002), Combining convergence and diversity in evolutionary multiobjective optimization, *Evol. Comput.*, *10*(3), 263–282.
- Liebman, J. (1976), Some simple-minded observations on the role of optimization in public systems decision-making, *Interfaces*, *6*(4), 102–108.
- Logar, I., and J. C. J. M. van den Bergh (2013), Methods to assess costs of drought damages and policies for drought mitigation and adaptation: Review and recommendations, *Water Resour. Manage.*, *27*, 1707–1720.
- Lopez, A., F. Fung, M. New, G. Watts, A. Weston, and R. L. Wilby (2009), From climate model ensembles to climate change impacts and adaptation: A case study of water resource management in the southwest of England, *Water Resour. Res.*, *45*, W08419, doi:10.1029/2008WR007499.
- Lund, J., and M. Israel (1995), Optimization of transfers in urban water supply planning, *J. Water Resour. Plann. Manage.*, *121*(1), 41–48.
- Lund, J. R. (1995), Derived estimation of willingness to pay to avoid probabilistic shortage, *Water Resour. Res.*, *31*(5), 1367–1372, doi:10.1029/95WR00481.
- Maier, H. R., et al. (2014), Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions, *Environ. Modell. Software*, *62*, 271–299, doi:10.1016/j.envsoft.2014.09.013.
- Manning, L. J., J. W. Hall, H. J. Fowler, C. G. Kilsby, and C. Tebaldi (2009), Using probabilistic climate change information from a multimodel ensemble for water resources assessment, *Water Resour. Res.*, *45*, W11411, doi:10.1029/2007WR006674.
- Marsh, T., G. Cole, and R. Wilby (2007), Major droughts in England and Wales, 1800–2006, *Weather*, *62*, 87–93, doi:10.1002/wea.67.
- Matrosov, E. S., S. Padula, and J. J. Harou (2013a), Selecting portfolios of water supply and demand management strategies under uncertainty—Contrasting economic optimisation and 'Robust Decision Making' approaches, *Water Resour. Manage.*, *27*(4), 1123–1148, doi:10.1007/s11269-012-0118-x.
- Matrosov, E. S., A. Woods, and J. Harou (2013b), Robust decision making and Info-Gap decision theory for water resource system planning, *J. Hydrol.*, *494*, 43–58.
- Matrosov, E. S., I. Huskova, J. R. Kasprzyk, J. J. Harou, C. Lambert, and P. M. Reed (2015), Many-objective optimization and visual analytics reveal key trade-offs for London's water supply, *J. Hydrol.*, *531*, 1040–1053, doi:10.1016/j.jhydrol.2015.11.003.
- Moody, P., and C. Brown (2012), Modeling stakeholder-defined climate risk on the Upper Great Lakes, *Water Resour. Res.*, *48*, W10524, doi:10.1029/2012WR012497.
- Moody, P., and C. Brown (2013), Robustness indicators for evaluation under climate change: Application to the upper Great Lakes, *Water Resour. Res.*, *49*, 3576–3588, doi:10.1002/wrcr.20228.
- Mortazavi, M., G. Kuczera, and L. Cui (2012), Multiobjective optimization of urban water resources: Moving toward more practical solutions, *Water Resour. Res.*, *48*, W03514, doi:10.1029/2011WR010866.
- Mortazavi-Naeini, M., G. Kuczera, and L. Cui (2014), Application of multiobjective optimization to scheduling capacity expansion of urban water resource systems, *Water Resour. Res.*, *50*, 4624–4642, doi:10.1002/2013WR014569.
- Mortazavi-Naeini, M., G. Kuczera, and L. Cui (2015a), Efficient multi-objective optimization methods for computationally intensive urban water resources models, *J. Hydroinf.*, *17*(1), 36–55.
- Mortazavi-Naeini, M., G. Kuczera, A. S. Kiem, L. Cui, B. Henley, B. Berghout, and E. Turner (2015b), Robust optimization to secure urban bulk water supply against extreme drought and uncertain climate change, *Environ. Modell. Software*, *69*, 437–451.
- Murphy, J. M., B. B. Booth, M. Collins, G. R. Harris, D. M. Sexton, and M. J. Webb (2007), A methodology for probabilistic predictions of regional climate change from perturbed physics ensembles, *Philos. Trans. R. Soc. A*, *365*(1857), 1993–2028.
- Murphy, J. M., et al. (2009), *UK Climate Projections Science Report: Climate Change Projections*, Met Off. Hadley Cent., Exeter, U. K.
- Nazemi, A., and H. S. Wheeler (2014), Assessing the vulnerability of water supply to changing streamflow conditions, *Eos Trans. AGU*, *95*(32), 288–289.

- Nazemi, A., H. S. Wheeler, K. P. Chun, and A. Elshorbagy (2013), A stochastic reconstruction framework for analysis of water resource system vulnerability to climate-induced changes in river flow regime, *Water Resour. Res.*, **49**, 291–305, doi:10.1029/2012WR012755.
- New, M., A. Lopez, S. Dessai, and R. Wilby (2007), Challenges in using probabilistic climate change information for impact assessments: An example from the water sector, *Philos. Trans. R. Soc. A*, **365**(1857), 2117–2131.
- Nicklow, J., et al. (2010), State of the art for genetic algorithms and beyond in water resources planning and management, *J. Water Resour. Plann. Manage.*, **136**(4), 412–432.
- O'Connell, P. E., and G. O'Donnell (2014), Towards modelling flood protection investment as a coupled human and natural system, *Hydrol. Earth Syst. Sci.*, **18**, 155–171, doi:10.5194/hess-18-155-2014.
- OECD (2013), *Water and Climate Change Adaptation: Policies to Navigate Uncharted Waters*, *OECD Studies on Water*, OECD Publishing, Paris, doi:10.1787/9789264200449-en.
- Padula, S., J. J. Harou, L. G. Papageorgiou, L. Ji, A. Mohammad, and N. Hepworth (2013), Least economic cost regional water supply planning: Optimizing infrastructure investments and demand management for South East England's 17.6 million people, *Water Resour. Manage.*, **27**(15), 5017–5044.
- Paton, F. L., H. R. Maier, and G. C. Dandy (2014a), Including adaptation and mitigation responses to climate change in a multiobjective evolutionary algorithm framework for urban water supply systems incorporating GHG emissions, *Water Resour. Res.*, **50**, 6285–6304, doi:10.1002/2013WR015195.
- Paton, F. L., G. C. Dandy, and H. R. Maier (2014b), Integrated framework for assessing urban water supply security of systems with non-traditional sources under climate change, *Environ. Modell. Software*, **60**, 302–319.
- Patskoski, J., and A. Sankarasubramanian (2015), Improved reservoir sizing utilizing observed and reconstructed streamflows within a Bayesian combination framework, *Water Resour. Res.*, **51**, 5677–5697, doi:10.1002/2014WR016189.
- Poff, N. L., et al. (2016), Sustainable water management under future uncertainty with eco-engineering decision scaling, *Nat. Clim. Change*, **6**, 25–34, doi:10.1038/nclimate2765.
- Randall, D., L. Cleland, C. Kuehne, G. Link, and D. Sheer (1997), Water supply planning simulation model using mixed-integer linear programming "engine", *J. Water Resour. Plann. Manage.*, **123**(2), 116–124.
- Ray, P., P. Kirshen, and D. Watkins Jr. (2012), Staged climate change adaptation planning for water supply in Amman, Jordan, *J. Water Resour. Plann. Manage.*, **138**(5), 403–411.
- Ray, P., D. Watkins Jr., R. Vogel, and P. Kirshen (2014), Performance-based evaluation of an improved robust optimization formulation, *J. Water Resour. Plann. Manage.*, 04014006, doi:10.1061/(ASCE)WR.1943-5452.0000389.
- Reed, P., and B. Minsker (2004), Striking the balance: Long-term groundwater monitoring design for conflicting objectives, *J. Water Resour. Plann. Manage.*, **130**(2), 140–149.
- Reed, P. M., and J. R. Kasprzyk (2009), Water resources management: The myth, the wicked, & the future, *J. Water Resour. Plann. Manage.*, **135**(6), 411–413.
- Reed, P. M., D. Hadka, J. Herman, J. Kasprzyk, and J. Kollat (2013), Evolutionary multiobjective optimization in water resources: The past, present, and future, *Adv. Water Resour.*, **51**, 438–456.
- Rocheta, E., M. Sugiyanto, F. Johnson, J. Evans, and A. Sharma (2014), How well do general circulation models represent low-frequency rainfall variability?, *Water Resour. Res.*, **50**, 2108–2123, doi:10.1002/2012WR013085.
- Singh, R., T. Wagener, R. Crane, M. E. Mann, and L. Ning (2014), A vulnerability driven approach to identify adverse climate and land use change combinations for critical hydrologic indicator thresholds: Application to a watershed in Pennsylvania, USA, *Water Resour. Res.*, **50**, 3409–3427, doi:10.1002/2013WR014988.
- Stainforth, D. A., M. R. Allen, E. R. Tredger, and L. A. Smith (2007), Confidence, uncertainty and decision-support relevance in climate predictions, *Philos. Trans. R. Soc. A*, **365**, 2145–2161.
- Stakhiv, E. Z. (2011), Pragmatic approaches for water management under climate change uncertainty, *J. Am. Water Resour. Assoc.*, **47**, 1183–1196, doi:10.1111/j.1752-1688.2011.00589.x.
- Steinschneider, S., and C. Brown (2012), Dynamic reservoir management with real-option risk hedging as a robust adaptation to nonstationary climate, *Water Resour. Res.*, **48**, W05524, doi:10.1029/2011WR011540.
- Steinschneider, S., and C. Brown (2013), A semiparametric multivariate, multisite weather generator with low-frequency variability for use in climate risk assessments, *Water Resour. Res.*, **49**, 7205–7220, doi:10.1002/wrcr.20528.
- Steinschneider, S., R. McCrary, S. Wi, K. Mulligan, L. Mearns, and C. Brown (2015), Expanded decision-scaling framework to select robust long-term water-system plans under hydroclimatic uncertainties, *J. Water Resour. Plann. Manage.*, 04015023, doi:10.1061/(ASCE)WR.1943-5452.0000536.
- Thames Water (2014), *Water Resources Management Plan 2015-2040*, Reading, U. K.
- Tingstad, A., D. Groves, and R. Lempert (2014), Paleoclimate scenarios to inform decision making in water resource management: Example from Southern California's inland empire, *J. Water Resour. Plann. Manage.*, **140**(10), 04014025.
- Tolson, B., H. Maier, A. Simpson, and B. Lence (2004), Genetic algorithms for reliability-based optimization of water distribution systems, *J. Water Resour. Plann. Manage.*, **130**(1), 63–72.
- Turner, S. W. D., D. Marlow, M. Ekström, B. G. Rhodes, U. Kularathna, and P. J. Jeffrey (2014), Linking climate projections to performance: A yield-based decision scaling assessment of a large urban water resources system, *Water Resour. Res.*, **50**, 3553–3567, doi:10.1002/2013WR015156.
- UKWIR (2002), *The Economic of Balancing Supply & Demand (EBSD)—Main Report*, London, U. K.
- UNISDR (2009), *UNISDR Terminology on Disaster Risk Reduction*, Geneva, Switzerland.
- U.S. Environmental Protection Agency (2012), Adaptation strategies guide for water utilities, *Rep. EPA 817-K-11-003*, Washington, D. C.
- Wade, S., J. Rance, and N. Reynard (2013), The UK Climate Change Risk Assessment 2012: Assessing the impacts on water resources to inform policy makers, *Water Resour. Manage.*, **27**, 1085–1109.
- Whateley, S., S. Steinschneider, and C. Brown (2014), A climate change range-based method for estimating robustness for water resources supply, *Water Resour. Res.*, **50**, 8944–8961, doi:10.1002/2014WR015956.
- Wilby, R. L. (2005), Uncertainty in water resource model parameters used for climate change impact assessment, *Hydrol. Processes*, **19**, 3201–3219, doi:10.1002/hyp.5819.
- Wilby, R. L., and I. Harris (2006), A framework for assessing uncertainties in climate change impacts: Low-flow scenarios for the River Thames, UK, *Water Resour. Res.*, **42**, W02419, doi:10.1029/2005WR004065.
- Wilby, R. L., B. Greenfield, and C. Glenny (1994), A coupled synoptic-hydrological model for climate change impact assessment, *J. Hydrol.*, **153**(1–4), 265–290.

- Wilby, R. L., C. R. Fenn, P. J. Wood, R. Timlett, and T. LeQuesne (2011), Smart licensing and environmental flows: Modeling framework and sensitivity testing, *Water Resour. Res.*, *47*, W12524, doi:10.1029/2011WR011194.
- Wu, W., H. R. Maier, and A. R. Simpson (2013), Multiobjective optimization of water distribution systems accounting for economic cost, hydraulic reliability, and greenhouse gas emissions, *Water Resour. Res.*, *49*, 1211–1225, doi:10.1002/wrcr.20120.
- Zeff, H. B., J. R. Kasprzyk, J. D. Herman, P. M. Reed, and G. W. Characklis (2014), Navigating financial and supply reliability tradeoffs in regional drought management portfolios, *Water Resour. Res.*, *50*, 4906–4923, doi:10.1002/2013WR015126.

Erratum

In the originally published version of this article, the unit of measure for the variable “cost” was incorrectly given as M£ in Figure 3, Figure 4, Figure 5, and Figure 7. The error has since been corrected and this version may be considered the authoritative version of record.