



## RESEARCH ARTICLE

10.1002/2014WR015558

## Key Points:

- Probability of exceeding planned frequency of water shortages is used as a risk metric
- Nonstationary climate projections used to estimate changes in the risk metric
- Use of uncertain climate information for adaptation planning is demonstrated

## Correspondence to:

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

## Citation:

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.

Received 8 MAR 2014

Accepted 1 AUG 2014

Accepted article online 5 AUG 2014

Published online 22 AUG 2014

This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

## Risk-based water resources planning: Incorporating probabilistic nonstationary climate uncertainties

Edoardo Borgomeo<sup>1</sup>, Jim W. Hall<sup>1</sup>, Fai Fung<sup>2</sup>, Glenn Watts<sup>2</sup>, Keith Colquhoun<sup>3</sup>, and Chris Lambert<sup>3</sup>
<sup>1</sup>Environmental Change Institute, University of Oxford, Oxford, UK, <sup>2</sup>Environment Agency, Horizon House, Bristol, UK,

<sup>3</sup>Thames Water, Clearwater Court, Reading, UK

**Abstract** We present a risk-based approach for incorporating nonstationary probabilistic climate projections into long-term water resources planning. The proposed methodology uses nonstationary synthetic time series of future climates obtained via a stochastic weather generator based on the UK Climate Projections (UKCP09) to construct a probability distribution of the frequency of water shortages in the future. The UKCP09 projections extend well beyond the range of current hydrological variability, providing the basis for testing the robustness of water resources management plans to future climate-related uncertainties. The nonstationary nature of the projections combined with the stochastic simulation approach allows for extensive sampling of climatic variability conditioned on climate model outputs. The probability of exceeding planned frequencies of water shortages of varying severity (defined as Levels of Service for the water supply utility company) is used as a risk metric for water resources planning. Different sources of uncertainty, including demand-side uncertainties, are considered simultaneously and their impact on the risk metric is evaluated. Supply-side and demand-side management strategies can be compared based on how cost-effective they are at reducing risks to acceptable levels. A case study based on a water supply system in London (UK) is presented to illustrate the methodology. Results indicate an increase in the probability of exceeding the planned Levels of Service across the planning horizon. Under a 1% per annum population growth scenario, the probability of exceeding the planned Levels of Service is as high as 0.5 by 2040. The case study also illustrates how a combination of supply and demand management options may be required to reduce the risk of water shortages.

## 1. Introduction

The increased awareness of the impacts of climate change on water resources [Kundzewicz *et al.*, 2008; Vörösmarty *et al.*, 2000] has generated interest in new methodologies to help water resources managers deal with uncertain information from climate models [e.g., Brown *et al.*, 2010; Groves *et al.*, 2008a]. Water planners recognize that information from climate models is highly uncertain but potentially useful and are now faced with the challenge of developing methodologies to use this uncertain information to assess climate change impacts and support their long-term planning strategies.

Hydrology is inherently uncertain, and water planners have since the 1980s dealt with uncertain hydrological information using stochastic approaches and risk-based criteria. Risk-based decision making involves comparing management options on the basis of their ability to reduce risks, alongside their economic and environmental costs. Applications of risk-based concepts in water resources management have ranged from water quality [McIntyre *et al.*, 2003b] to reservoir operation and control [Nardini *et al.*, 1992; Simonovic *et al.*, 1992] problems. Traditional applications of risk-based principles and stochastic approaches to water planning used statistics of the historical record to estimate flow frequencies and probabilities of system failure [e.g., Hirsch, 1978; Hashimoto *et al.*, 1982; McIntyre *et al.*, 2003a; Wagner *et al.*, 1988].

These approaches are based on the fundamental assumption of hydrological stationarity, which, it is argued, is no longer tenable for water planning in a changing climate [Milly *et al.*, 2008; Brown 2010]. Therefore, water planners need to revise current planning approaches to identify “non-stationary probabilistic models of hydrological variables” [Milly *et al.*, 2008]. Abandoning stationarity, however, raises profound challenges for water planners and the research community because it excludes conventional methods for estimating statistics. In the absence of such information, water planners are faced with the challenge of

choosing the conditions under which to test their systems and make the most out of those few limited sources of evidence at their disposal, namely observed records of the past and climate model projections of the future, while being cognizant of the limitations and uncertainties associated with both of these sources of evidence. For instance, different ways of estimating potential evapotranspiration (PET) add uncertainty to the observed record, while choices about climate model structure (e.g., processes included, grid resolution, and subgrid scale parameterization) add uncertainty to projections of future climate.

In recent years, a large number of studies have tried to address this challenge and use uncertain data from climate models in hydrological impact assessments. The majority of studies have downscaled outputs from global circulation models (GCMs) to project hydrological variables at a basin scale and have tried to characterize uncertainty using ensembles of GCMs [e.g., *Horton et al.*, 2006; *Christensen and Lettenmaier*, 2007; *Lopez et al.*, 2009; *Fung et al.*, 2013]. Such approaches often use quasi-stationary projections, which create stationary series of weather variables for specified “time slices” in the future. The availability of climate model ensembles has led to new methodologies for quantifying uncertainty in future climate projections in a probabilistic way [e.g., *Murphy et al.*, 2007; *Tebaldi and Knutti*, 2007]. Ensembles of climate projections have been used within a risk-based approach to assess reservoir operation risk in California [*Brekke et al.*, 2009] and supply failure risk in the southwest of England [*Lopez et al.*, 2009].

The latest UK Climate Projections (UKCP09) are based on a large perturbed physics ensemble of the Met Office Hadley Centre’s HadCM3 GCM [*Murphy et al.*, 2009]. These climate projections are an important step forward in their Bayesian estimation of climate model uncertainties, based on model skill at reproducing observed weather variables for regions of the world, as well as incorporating evidence on future uncertainties derived from the spread of GCM predictions from different climate modeling centers around the world [*Murphy et al.*, 2009].

The UKCP09 projections are accompanied by a weather generator (WG) that can be used to simulate synthetic time series of weather variables (including precipitation and temperature) for individual locations ( $5 \times 5$  km grid squares) based on a stochastic process representation calibrated to present day climate [*Kilsby et al.*, 2007]. Change factors are obtained from the climate model output by measuring the difference in the statistics of relevant weather variables estimated from the modeled baseline and the projection for a given decade in the future. Change factors may be expressed as absolute differences or as percentage changes. Sampling of different vectors of change factors provides the opportunity to explore epistemic uncertainties in future climate, while repeated realizations of the WG with the same parameterizations allow sampling of natural variability. The UKCP09 probabilistic projections have been recognized as a useful tool for climate change impact assessments and adaptation decision making [*Hall et al.*, 2012; *Christierson et al.*, 2012].

Probabilistic climate information such as UKCP09 has already been used for climate change impact assessments in the water sector. For example, *New et al.* [2007], *Manning et al.* [2009], and *Groves et al.* [2008b] used probabilistic climate change information from multimodel climate ensembles to estimate future water availability. *Christierson et al.* [2012] used the UKCP09 to project future river flows across the UK. While these studies provided projections of future water availability and demonstrated the value of climate model information for water planning, they are restricted to hydrological assessment of the impacts of climate change without extending the analysis to more decision-relevant risk metrics, or appraising adaptation options in terms of their potential to reduce the risks of a water shortage [*New et al.*, 2007]. Only a few studies have tried to use probabilistic climate projections to estimate changes in decision-relevant variables. *Wilby et al.* [2011] used the UKCP09 to assess changes in the frequency of harmful environmental flows.

The main aim of this paper is to develop a risk-based framework for (i) incorporating nonstationary probabilistic climate information in water resources planning, (ii) addressing multiple sources of uncertainty simultaneously, and (iii) testing different adaptive water resources management options under continuously changing nonstationary climate conditions. To achieve this we demonstrate (1) how nonstationary probabilistic climate projections, combining a stochastic process representation with change signal from a climate model ensemble, can be used to generate probabilistic distributions of decision-relevant variables; (2) how a probabilistic metric of the system’s ability to meet required Levels of Service (LoS), defined as “the planned average frequency of customer demand restrictions” [UKWIR, 2012], provides a way of summarizing uncertainties in supply and demand, including uncertainty in climate projections. The use of a risk metric provides a criterion for choosing between alternative water resources management plans. We thereby provide a

means of adapting methodologies for risk-based water resources management to cope with a nonstationary climate. While sharing some similarities with sensitivity analysis approaches that have been previously proposed (e.g., vulnerability analysis [Nazemi *et al.* 2013] or decision-scaling [Brown *et al.*, 2012; Brown and Wilby, 2012; Turner *et al.*, 2014]), our risk-based framework provides a more explicit link to decision making, a point we return to in section 4.2 of this paper.

In developing this approach, we must recognize the uncertainties associated with the probability distribution of future climate change projections, such as those provided by UKCP09. Any such probability distribution is conditional on a set of modeling and other methodological assumptions, along with assumed greenhouse gas emissions trajectories, which are bound to be updated as new knowledge emerges [Stainforth *et al.*, 2007; Hall, 2007]. Yet if a given distribution encodes the current state of knowledge (including knowledge about uncertainties), it is rational for a decision maker to use it, while being conscious of the need to explore and ensure robustness to unmodeled uncertainties. Thus, any probabilistic analysis of the type described in this paper should be accompanied by analysis of the sensitivity of decisions to distributional assumptions.

The paper is structured in five sections. Section 2 describes the proposed risk-based water resources planning methodology. In section 3, the risk-based approach is applied to a simplified version of a water resource system that serves the city of London (UK). The case study illustrates how thinking of water resources planning in terms of risk allows for a more explicit representation of the role of different factors and relative uncertainties in influencing the occurrence of undesired outcomes. In section 4, the framework's limitations and challenges in implementation are discussed and conclusions are drawn in section 5.

## 2. Methodology

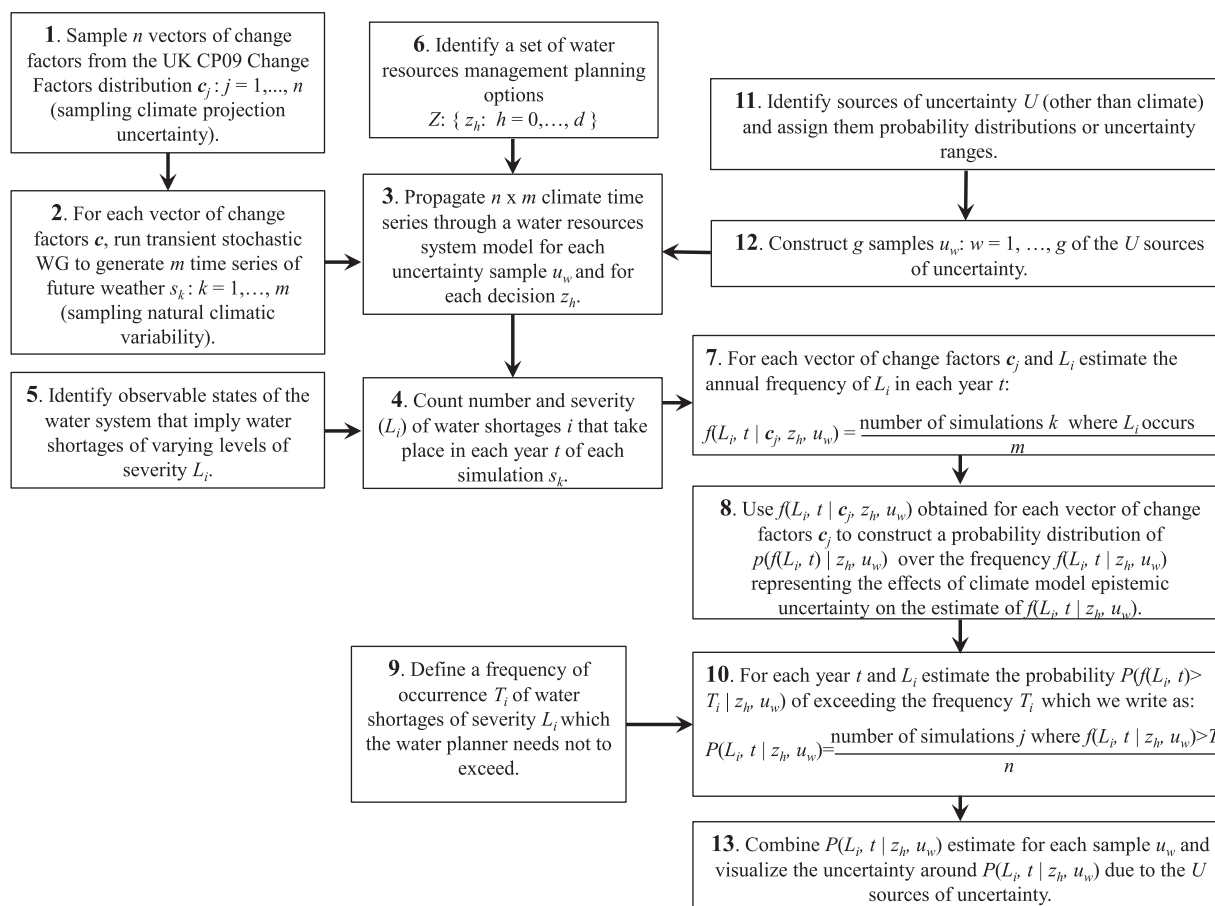
The methodology presented here seeks to demonstrate how risk concepts offer a means of incorporating probabilistic climate information in long-term water resources planning. In doing so, this approach introduces a risk metric that can be directly related to the frequency of water shortages experienced by water users, which is calculated by continuous simulation of the water system, driven by nonstationary climate variables obtained via a modified version of the UKCP09 stochastic weather generator.

Figure 1 shows a flowchart of the proposed methodology. The methodology is based on multiple stochastic realizations of future series of climate variables conditioned on vectors of change factors obtained from climate models (boxes 1 and 2). Hydrological and water system simulations (boxes 3 and 4) predict observable states of the system that trigger increasingly severe restrictions on water use (water shortages, box 5) for each future climate realization for a set of water resources management actions (box 6). The output from each simulation is a record of the frequency of water shortages in the simulation period. Repeated stochastic climate realizations conditioned on the same vector of change factors will yield a record of the frequency of water shortages in the simulation period (box 7). The frequencies obtained for each vector of change factors can then be combined to construct a probability distribution of the frequency of water shortages (box 8), which can be compared to the planned frequency of customer demand restrictions (the LoS in box 9) to estimate the probability of exceeding the LoS frequency (box 10). These simulation steps can be repeated to test the effects of nonclimate-related uncertainties (boxes 11 and 12) on the probability of exceeding the planned LoS (box 13).

The risk-based approach follows four steps which are described in detail below.

### 2.1. Estimating Frequencies of Water Shortages

Water resources studies have traditionally focused on rather abstract quantities, such as water availability or margins between supply and demand. These quantities are abstract because they cannot be directly related to observable states of the system. In the risk-based approach proposed here, we focus on the likelihood and consequences of observable undesired outcomes. In the case of water resources management, the outcomes of interest to water users are water shortages of different levels of severity, which are triggered by observable states of the system that can be directly measured. The observable states of the system that trigger water shortages and associated water use restrictions depend on the characteristics of the system, but are typically observed reservoir or groundwater levels. In the context of the case study presented in the



**Figure 1.** Methodology flowchart for estimating the probability of exceeding a given frequency of a water shortage using probabilistic climate projections.

next section, different reservoir storage levels are used to define water shortages of different severity that trigger water use restrictions.

For domestic water users, water shortages may materialize as restrictions on particular types of water uses (e.g., the use of hosepipes for garden watering) and, in the worst cases, as severe water rationing. For agricultural and industrial users, shortage events materialize when abstraction restrictions are applied. The application of abstraction restrictions will typically incorporate consideration of the requirements to preserve environmental flows.

While water users would rather not incur restrictions on water use, it is recognized that 100% reliability of water supply is not achievable, given the inherent variability in hydrological conditions. Water users have been extensively surveyed to explore the frequency of shortages that they will tolerate and their willingness to pay to reduce the frequency of shortages [Hensher et al., 2006; Willis et al., 2005]. On the basis of this empirical evidence, and the estimated cost of reducing the frequency of shortages, water utilities establish the planned frequency of customer demand restrictions, for shortages of varying severity, which are known as Levels of Service (LoS) which can be regarded as the thresholds of acceptable risk of water shortage for water users.

Table 1 gives an example from the Thames catchment of the type of water use restrictions and frequencies associated with different LoS. In this case, each one of four water use restrictions is triggered by the reservoir storage falling below a specified level. The restriction is introduced to reduce demand and hence the likelihood of further restrictions becoming necessary. Table 1 also reports the empirical evidence of the amount of demand reduction achieved by water use restrictions in the Thames catchment [Thames Water, 2013].

**Table 1.** Four Levels of Water Use Restriction With Their Corresponding Frequencies of Occurrence and Expected Demand Savings [Thames Water, 2013]

Level of Service ( $L_i$ )	Frequency of Occurrence	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	"Never"	Emergency Drought Order for standpipes and rota cuts	31.3

Given a stationary climate with well-understood and characterized natural variability, and with all other factors, such as demand, remaining constant, it would be possible to estimate the frequency with which given levels of shortages occur and compare these with the LoS. Under stationary conditions, a system with known characteristics will either meet or fail to meet its LoS. However, in the context of uncertain hydrological conditions (at present and more so in the future), the most it will be possible to do is estimate the probability of a LoS being met or not. The probability of failing to meet LoS, for different years in the future, which will change in a nonstationary climate, is our proposed metric of water resource system risk.

We then analyze the impact on this metric of a set  $Z = \{z_h; h = 0, \dots, d\}$  of future water resources management options, in the context of  $U = \{u_w; w = 1, \dots, g\}$  sources of nonclimate-related uncertainties (boxes 11 and 12 in Figure 1). Decisions can include supply and demand management options. Combinations of options may differ not just in the combination of different measures but also in the sequence through the simulation period in which they are implemented (i.e., different adaptation pathways). For supply-side options, the available capacity and the time of implementation within the simulation period should be identified. Similarly, for demand-side options, the expected reductions in demand should be determined.

The analysis is carried out using a water resource system simulation model that can (i) propagate synthetic weather series through to river flows and groundwater levels, (ii) resolve the operation of the water resources system and the observable states of the system that trigger water use restrictions, (iii) simulate the effects of water use restrictions on demand, and (iv) incorporate the effects of uncertainties  $U$ , including hydrological model and demand-side uncertainties.

## 2.2. Integrating Uncertainty in Climate Projections

In this study, future climate conditions are obtained using synthetic time series generated with a stochastic weather generator (WG) based on the UKCP09 probabilistic climate projections. In this section, we describe the characteristics of the UKCP09 projections, but our proposed methodology could also be implemented using different types of probabilistic climate change information generated from ensembles of GCMs (e.g., [Tebaldi *et al.*, 2005; Groves *et al.*, 2008b]).

The UKCP09 probabilistic projections were constructed by applying a Bayesian framework to estimate climate model uncertainty. In this framework, climate model parameter uncertainty is explored via a perturbed physics ensemble (PPE) of the HadCM3 climate model, whereas uncertainty arising from structural errors present in the HadCM3 model is incorporated via two approaches [Murphy *et al.*, 2009]. (1) The scenarios are driven by a perturbed physics ensemble (PPE) of 280 runs of the equilibrium response to double  $\text{CO}_2$  carried out using the HadSM3 GCM, which sampled the 31 parameters controlling the surface and atmospheric processes most important for the simulation of (both global and regional) climate. Some of these parameters include "switches" between different model structural formulations, so are sampling model structural uncertainty. This large ensemble is augmented by a smaller ensemble of transient runs of the regional model configuration of HadCM3 exploring uncertainties in atmospheric, oceanic, sulphur cycle, and ecosystem processes. (2) A statistical emulator of the PPE simulations was used to predict the results of 12 members of a multimodel ensemble (MME) developed at other modeling centers, and containing structural assumptions partially independent of HadCM3. Results from these different simulations are incorporated in the Bayesian framework using a discrepancy factor, which measures the difference between the nearest PPE member generated from the Hadley Centre model and each member of the MME, where each MME is taken as a proxy of the true climate [Sexton *et al.*, 2012]. This discrepancy factor is used to quantify

**Table 2.** Weather Variables Contained in the Vector of Change Factors and Application Method

Climate Variable	Application Method
Precipitation average (mm)	Multiplication
Precipitation variance (mm)	Multiplication
Precipitation probability dry	Multiplication applied to logit transform
Precipitation skew	Multiplication
Precipitation lag-1 correlation	Multiplication applied to Fisher Z transform
Temperature average (°C)	Addition
Temperature variance (°C)	Multiplication
Temperature minimum (°C)	Addition
Temperature maximum (°C)	Addition
Sunshine average	Addition
Vapor pressure average (hPa)	Addition

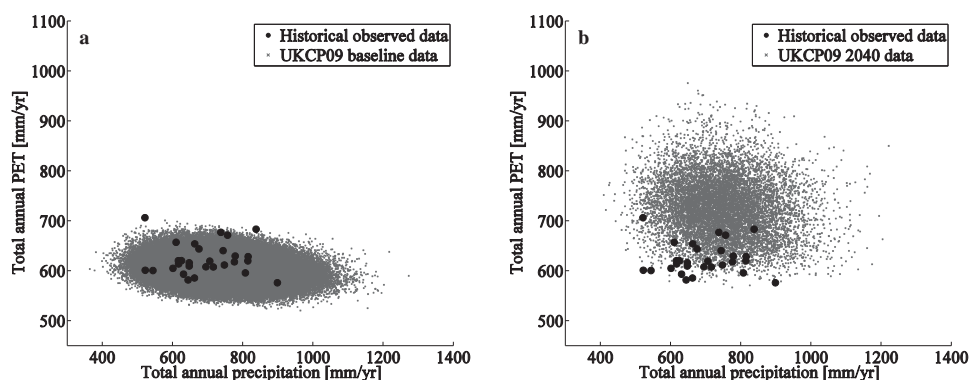
climate model structural error and is factored into the weights for different combinations of parameter values used to generate the projections.

The UKCP09 projections generate probability distributions of change factors, which measure the change in climate variables (temperature, precipitation, air pressure, and humidity) relative to the baseline (1961–1990) for  $25 \times 25$  km grid squares. A WG is provided with the UKCP09 projections to generate time series of weather variables at a resolution of 5 km. The UKCP09 WG uses a five parameters Neyman-Scott Rectangular Process model to simulate future precipitation series [Kilsby *et al.*, 2007]. Other climate

variables (i.e., temperature, sunshine) are determined via regression with the precipitation states. The WG is calibrated to achieve the best fit to the baseline climatology for each selected grid square, while the same change factors are applied to each of the  $25 \times 25$  km squares in each 25 km RCM grid square. Table 2 lists the variables in the vector of change factors and the method by which these change factors are applied to the WG parameters, on a calendar month basis.

The UKCP09 WG produces stationary time series representative of 30 year time slices, thus making it difficult to test water management strategies in a changing and nonstationary climate [Hall *et al.*, 2012]. To overcome this limitation, we generate weather variables for the period 1961–2060 with a stochastic weather generator consistent with the UKCP09 but which allows for the generation of transient time series over longer timescales (V. Glenis *et al.*, A stochastic weather generator for transient probabilistic climate scenarios derived from a large perturbed physics ensemble, submitted to *Advances in Water Resources*, 2014). Transient future climate conditions were obtained by generating stationary simulations for given months and decades and then concatenating them together to generate series which are nonstationary on a multidecadal timescale. The stochastic variability in the generated series and the slow rate of change in the change factors mean that the discontinuity in the simulated weather variables due to the method of concatenation is not noticeable. This methodology is limited in that nonstationarity is represented by introducing a trend in parameter values that are stationary at the decadal scale for given months of the year. Truly nonstationary time series could be generated by introducing time-dependent parameters in the WG; however, this approach is not compatible with the UKCP09 WG. These transient scenarios provide the information to model the system's response to stochastic nonstationary climatic conditions.

Our analysis framework involves simulation of time series of precipitation and PET by running  $m$  realizations of the stochastic WG. We assume that the baseline period (1961–1990) is stationary and match the statistics of the stationary WG to the estimated statistics of the observed weather data for this period. The assumption that the baseline (1961–1990) is stationary is based on the lack of long-term trends in annual rainfall totals for England [Marsh *et al.*, 2007; Perry, 2006]. Each set of future realizations  $s_k$ ;  $k = 1, \dots, m$  is conditioned on  $\mathbf{c}_j$ ;  $j = 1, \dots, n$  different vectors of change factors obtained from the UKCP09 projections. Each vector  $\mathbf{c}_j = (\mathbf{c}_{j,2020}, \mathbf{c}_{j,2030}, \mathbf{c}_{j,2040}, \mathbf{c}_{j,2050})$  is a time coherent series of future changes obtained using the method proposed by Glenis *et al.* (submitted manuscript, 2014), for a total of  $m \times n$  transient future climatic conditions. Downscaled GCMs projections typically have significant biases and may not represent the full range of climate variability and thus it has been argued that they do not provide a dependable basis for the analysis of climate risks [Brown *et al.*, 2012]. The sampling of uncertainty in UKCP09 is much more extensive than in other downscaled climate model exercises, providing a more robust test of the sensitivity of water resources systems to potential future climate conditions. A Monte Carlo sample of 10,000 different vectors of change factors has been generated in the UKCP09 projections. An example of the range of future climate conditions projected by UKCP09 for the Thames catchment at Kingston is given in Figure 2, which shows annual totals of precipitation and PET for the 1961–1990 observed record and for the UKCP09 baseline data (Figure 2a) and for the UKCP09 projections for 2040 (Figure 2b). For historical rainfall and PET, the observed data lie within the cloud of the UKCP09 simulations for the baseline. For the 2040s, the UKCP09 projections



**Figure 2.** Variability of total annual precipitation and PET for the historical (1961–1990) data: (a) UKCP09 baseline data and (b) UKCP09 2040 projections.

indicate an overall increase in PET across the ensemble, while the projected change in precipitation is more uncertain.

### 2.3. Estimating the Probability of Failing to Meet Levels of Service

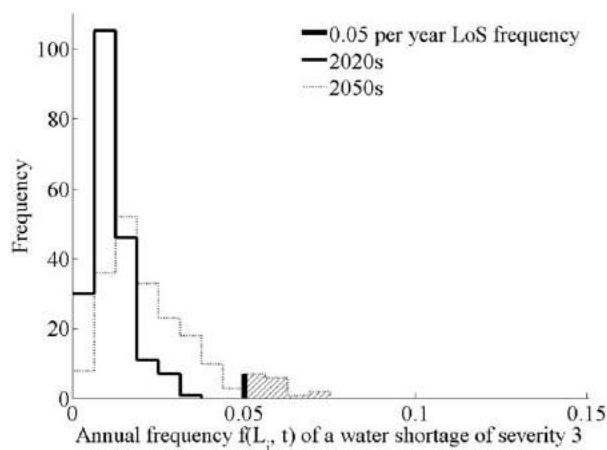
The water resources system model is run with the time series of future weather conditions and the number of times a water shortage of severity  $L_i$  occurs (i.e., a certain storage level is exceeded) in each year  $t$  of the simulation for each simulation  $k$  is recorded. The water resources system model is run for  $s_k$ :  $k = 1, \dots, m$  simulations conditioned on a change factor  $c_j$  to estimate the frequency  $f(L_i, t | c_j, z_h, u_w)$  of a water shortage of severity  $L_i$  in each year  $t$  for each for management option  $z_h$  and sample  $u_w$  of a nonclimatic source of uncertainty. This frequency is obtained by dividing the number  $k$  of simulations in which  $L_i$  occurs in year  $t$  by the total number of simulations  $m$ .

Running the water resources system model for a set of  $n$  equiprobable climatic change factors  $c_j$ :  $j = 1, \dots, n$  allows for the construction of a histogram of the frequency  $f(L_i, t | z_h, u_w)$  of a water shortage of severity  $L_i$ . This histogram represents the uncertainty around the  $f(L_i, t | z_h, u_w)$  estimate due to epistemic uncertainty in future climate projections. An example of a typical distribution for the frequency of a water shortage is shown in Figure 3. This example is based on a system where the LoS for a severity 3 shortage is set to 0.05 per year. The black vertical line in Figure 3 represents this frequency  $T_i$ . The probability of exceeding the LoS is estimated as the proportion of simulated instances  $m$  that exceeds  $T_i$  (the dashed area in Figure 3). This probability  $P(f(L_i, t) > T_i | z_h, u_w)$  of exceeding the frequency  $T_i$  in a year  $t$  for a water shortage of severity

$L_i$ , which we write as  $P(L_i, t | z_h, u_w)$ , is the risk metric that we use to compare alternative management strategies under future climatic conditions.

Figure 3 shows how the probability of exceeding  $T_i$  changes from the 2020s to the 2050s, reflecting the projected spread in future climatic conditions. The simulation is repeated for each management option  $z_h$  and the performance of each decision in terms of its ability to reduce the probability of failing to meet the LoS frequency is recorded.

As illustrated in boxes 11 and 12 in Figure 1, the process can



**Figure 3.** Typical simulation output showing the annual frequency of a water shortage of severity  $L_3$  for two different decades. This histogram is compared with the 0.05 line representing the Level of Service frequency for this severity  $L_i$  shortage to estimate the probability of exceeding the planned Level of Service (LoS).

be repeated to test the effects of other (i.e., nonclimate-related) uncertainties  $U$  on the probability of exceeding the planned LoS. These sources of nonclimatic uncertainty include, for example, hydrological model uncertainties, demand uncertainties due to population changes, or changes in environmental flow requirements. For instance, hydrological model uncertainties can be represented with probability distributions or likelihood weighted distributions of catchment runoff based on model uncertainty analysis [e.g., *Beven and Binley, 1992; Vrugt et al., 2003; Montanari and Brath, 2004*]. Where probability distributions are not known or where just the sensitivity to a few changes needs to be tested, uncertainties can be represented with scenarios. This may be the case, for example, for testing the impacts of changes in the amount of permitted abstraction on the risk of failing to meet the LoS. The flexibility of the approach allows for future quantifications of uncertainty and new information to be easily accommodated within this simulation framework.

By sampling from probability distributions or scenarios,  $u_w$ :  $w = 1, \dots, g$  samples of these nonclimate-related uncertainties are constructed and the water resources system model is run to estimate  $P(L_i, t | z_h, u_w)$  for each  $u_w$  sample. Repeated simulations of the water system for different  $u_w$  samples yield a distribution of the risk estimate, which reflects the impacts of  $U$  sources of uncertainty on  $P(L_i, t)$  and allows for testing the sensitivity of the system to nonclimatic uncertainties.

#### 2.4. Testing Management Options

The final step in the methodology involves making a risk-based decision and exploring the robustness of this decision to residual uncertainties and changes in model assumptions. Risk-based decision making involves comparing a set of options based on their potential to reduce risk and on their economic costs and environmental and sustainability impacts.

The identification of a tolerable probability of failing to meet a LoS is linked to the process of defining the LoS. As suggested by *Hall et al. [2012]*, there is a trade-off between a LoS and the probability of exceeding it, because the lower the planned maximum frequency of water shortages for a given LoS, the higher the probability of exceeding it. By considering the risk estimates from the simulation study, water resources managers can understand the LoS that can be expected from the water resource system and interact with water users to define the LoS accordingly.

Once a tolerable risk threshold is defined, the risk estimates obtained from the simulation for each decision  $z_h$  can be compared and candidate strategies can be selected based on their ability to cost-effectively reduce  $P(L_i, t)$ . The selection of the risk reduction strategy will depend on the costs  $a(z_h, u_w, t)$  of the decision, discounted over an appropriate time horizon, and the benefits  $b(z_h, u_w, t)$  that the strategy achieves for a given set of uncertain conditions  $u_w$ , where the benefit can be defined in terms of the change in risk relative to the baseline:

$$b(z_h, u_w, t) = P(L_i, t | z_0, u_w) - P(L_i, t | z_h, u_w) : h = 0, \dots, d \quad (1)$$

where  $z_0$  depicts the case in which there is no intervention. Each decision will have associated costs, for instance the capital costs of infrastructure development, operational expenditure, environmental impacts, and externalities. In this framework, the decision problem becomes one of minimizing cost subject to achieving the required LoS with some target probability  $P^l(L_i)$ :

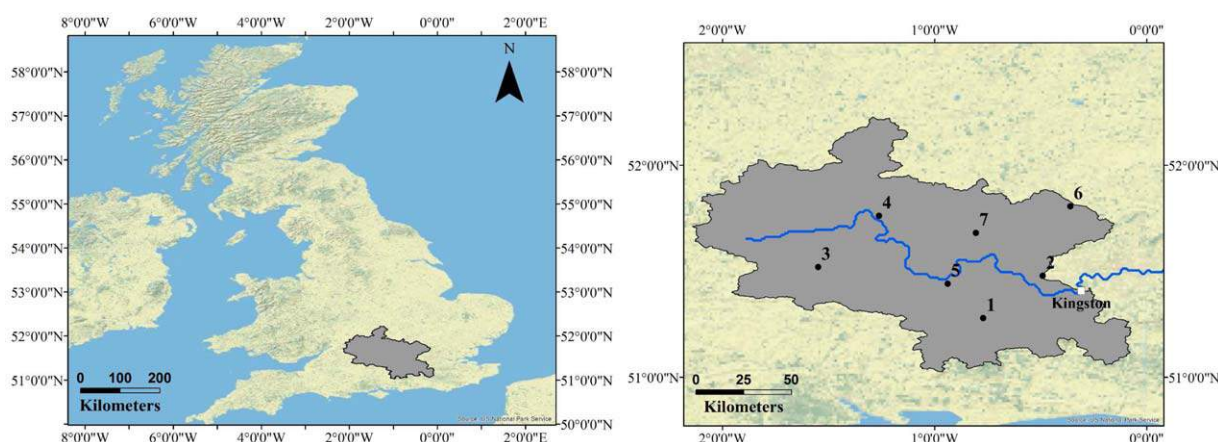
$$\min_h \sum_{t=1}^T D_t a(z_h, u_w, t) : P(L_i, t | z_h, u_w) < P^l(L_i) \forall t \in T \quad (2)$$

where  $D_t$  is a discount factor. This still leaves the question of what value of  $u_w$  to adopt. Prudent decision makers will explore a range of values of  $u_w$  and depending on their attitude to uncertainty identify a decision that more or less robustly achieves the frequency for a planned LoS. Furthermore, we note that while this decision is framed as a cost minimization problem, it can be regarded as a robust optimization as the optimization takes place with respect to conditions in the tail of a distribution of future possibilities (assuming that  $P^l(L_i)$  is small), so seeks to robustly achieve the target subject to some small residual risk of failing to meet this target.

### 3. Case Study

#### 3.1. Background

In England, water utility companies produce a water resources management plan every 5 years where they describe the actions they plan to take to ensure security of supply for the next 25 years. These plans are



**Figure 4.** Location map of (left) the Thames catchment and (right) the river flow gauging station and the weather stations in Table 4.

produced in consultation with the Environment Agency (the environmental protection and regulation agency in England). This 5 year cycle provides a water governance structure within which the current state of knowledge about the hydrological regime, water demands, and management options can be revisited and plans can be modified and adapted accordingly.

Water resources management plans in England and Wales are developed at a water resources zone level (WRZ). A WRZ describes an area where management of supply and demand is self-contained and where supply infrastructures and demand nodes are integrated, so that water users within the same WRZ experience the same risk of water shortages [Environment Agency, 2012]. A simplified representation of the London WRZ is used in this study.

The London WRZ covers the most densely populated area of the Thames catchment, which has an area of 9948 km<sup>2</sup> and is located in the south east of England (Figure 4). The Thames catchment has been classified as a seriously water stressed region by the Environment Agency [2008] and river flow projections for the area suggest that climate change could cause increased PET throughout the year and reductions in summer flows [Diaz-Nieto and Wilby, 2005; Manning et al., 2009], increasing the region's vulnerability to water stresses.

The London WRZ is supplied primarily by surface water abstraction from the river Thames, directly or via pump storage reservoirs, and by groundwater abstraction from the Chalk Aquifer [Thames Water, 2013]. Water supply in the area is managed by Thames Water Utilities Ltd, a private water utility company which serves approximately 7 million people in this WRZ alone. Public water supply is the only water use in the London WRZ. Surface water abstraction to meet public water demand is subject to a maximum limit, which is set to maintain environmental flows. Water resources managers in the area have identified climate change, population growth, and abstraction allowances reductions as the factors that will pose the greatest pressures on the reliability of the water resources system in the future.

### 3.2. Sources of Uncertainty

Our framework is intended to accommodate probabilistic representation of the most influential sources of uncertainty in water resources planning decisions. It is important to document all possible sources of uncertainty and also to evaluate the validity of uncertainty quantification. Table 3 lists several conceivable sources of uncertainty and indicates which ones have been addressed and how they have been addressed in this case study. We consider uncertainties related to the following factors: (i) natural climatic variability and climate projection uncertainty (including contributions from GCMs and RCM downscaling) are represented using the UKCP09 probabilistic projections, (ii) hydrological model parameter uncertainty is accounted for by sampling likely parameter ranges [Beven and Binley, 1992], (iii) population and the possibility of water abstraction licenses being reduced to enhance environmental flows (so-called sustainability reductions) are represented with scenarios. Emission scenario uncertainty, hydrological model structural uncertainty, and

**Table 3.** Examples of Sources of Uncertainty in Water Resources Management and Methods Taken to Address Them in the Case Study

Source of Uncertainty	Method
Climate variability	Stochastic realizations of WG
Climate model structural uncertainty	Multimodel ensemble. Perturbed physics ensemble
Climate model parameter uncertainty	Perturbed physics ensemble
Emission uncertainty	Not addressed
PE estimation uncertainty	Not addressed
Hydrological model parameter uncertainty	Sampling parameter ranges
Land use change uncertainty	Not addressed
River discharge observation uncertainty	Not addressed
Environmental flow allocation uncertainty	Scenario
Population growth uncertainty	Scenario
Climate impacts on demand uncertainty	Not addressed

uncertain land use changes are among the uncertainties not considered in the case study. We note that the sources of uncertainty not addressed in this study can be accommodated in the framework by repeating the steps in boxes 11 and 12 in Figure 1 for each source of nonclimate-related uncertainty.

### 3.3. Climate Change Projections

Future climate conditions were

obtained by running 100 repeated realizations  $k$  of the stochastic WG conditioned on 100 different vectors of change factors  $\mathbf{c}_j$  sampled from the full range of the UKCP09 probability distribution, resulting in a total 10,000 Monte Carlo samples of future climates. The WG provides daily time series of rainfall and PET which are nonstationary over the period 2001–2060.

The UKCP09 WG generates weather sequences for single  $5 \times 5$  km grid cells, or aerielly averaged over specified areas (e.g., catchments) [Jones *et al.*, 2009]. Analysis of observed precipitation from weather stations in the Thames catchment (Figure 4) reveal them to be highly correlated in space at a monthly scale (Table 4), so we have configured the WG to provide aerielly averaged inputs of the Thames catchment at Kingston.

Figures 5 and 6 show two sets of  $m = 100$  different time series realizations conditioned on two different vectors of change factors  $\mathbf{c}_j$ ;  $j = 1, 2$  for PET and precipitation annual totals respectively for the Thames catchment at Kingston. The shaded areas represent the full range of 10,000 climate projections derived from the WG, incorporating climate model uncertainty and natural variability. The insets show the annual total PET and precipitation probability distributions for three different decades for the two change factors  $\mathbf{c}_j$ . These probability density functions were generated by running 100 repeated realizations of a stochastic process conditioned on the same change factor  $\mathbf{c}_j$ .

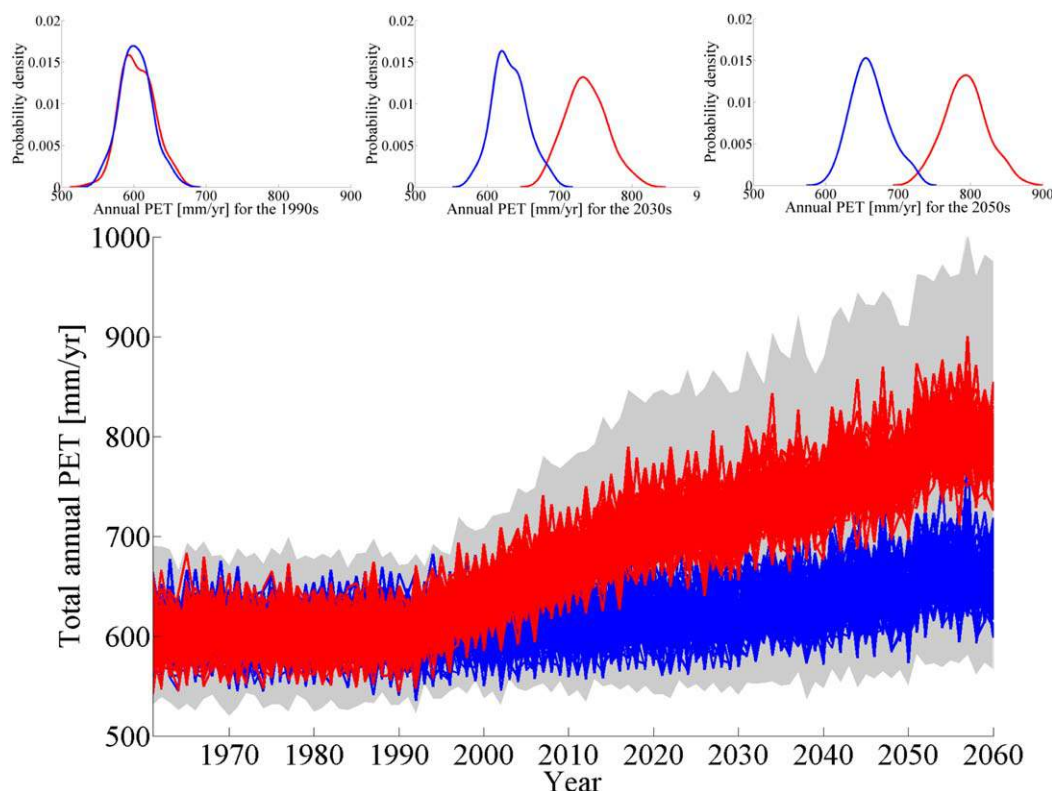
The PET projections (Figure 5) show an increasing spread through the century, reflecting a progressive departure away from the baseline conditions (1961–1990). The precipitation projections in Figure 6 do not show the same level of divergence away from the present into the future. This is due to the higher interannual variability in the precipitation data, which hides the climate signal contained in the different change factor samples. The projections indicate an increase in PET annual totals across the whole ensemble, whereas rainfall projections show both decreases and increases, which is consistent with projections for the area obtained using different climate change information [e.g., Diaz-Nieto and Wilby, 2005].

The UKCP09 projections are presented for three different emission scenarios (high, medium, and low). In this study, a medium emission scenario is selected and uncertainty associated with this choice is not assessed. This choice has little effect on the final results as differences between the projections based on the three emission scenarios are small up to the 2030s [Hall *et al.*, 2012].

**Table 4.** Correlation Matrix for the Seven Weather Stations Shown in Figure 4<sup>a</sup>

Map ID	Station	Farnborough	Heathrow	Upper Lambourn	Oxford	Reading	Rothamsted	High Wycombe
1	Farnborough	1	0.920	0.871	0.846	0.936	0.902	0.912
2	Heathrow	0.998	1	0.820	0.851	0.931	0.904	0.897
3	Upper Lambourn	0.998	0.997	1	0.895	0.899	0.856	0.902
4	Oxford	0.998	0.997	0.999	1	0.899	0.864	0.900
5	Reading	0.999	0.998	0.998	0.998	1	0.906	0.936
6	Rothamsted	0.997	0.997	0.997	0.998	0.997	1	0.927
7	High Wycombe	0.998	0.997	0.998	0.999	0.998	0.998	1

<sup>a</sup>Upper diagonal shows correlations for monthly precipitation totals and lower diagonal shows correlations for monthly PET totals for the baseline (1961–1990).



**Figure 5.** Total annual PET generated with the stochastic WG. Shaded areas represent full range of projections; blue and red lines represent 100 realizations from two different vectors of change factors  $c_j$ . Insets illustrate the probability density functions for the two change factors for annual PET for the Thames at Kingston.

### 3.4. Hydrological Modeling

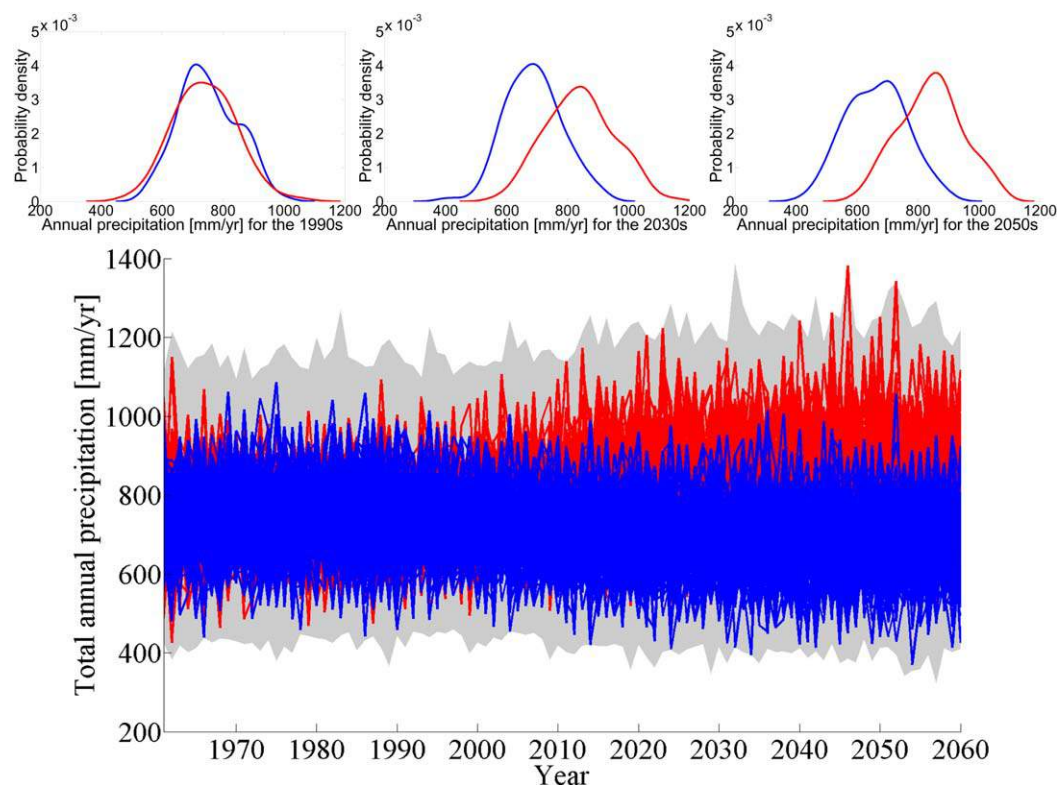
River flow was simulated using CATCHMOD, a rainfall-runoff model developed by the Environment Agency [Wilby *et al.*, 1994], which has been used extensively for water resources assessment and climate change impact studies in the Thames catchment [Wilby, 2005; Wilby and Harris, 2006; New *et al.*, 2007; Manning *et al.*, 2009]. CATCHMOD converts daily rainfall and PET time series into daily stream flow by subdividing the catchment into runoff zones. A more detailed description of the model structure can be found in Wilby *et al.* [1994].

The Thames catchment was divided into three zones: a slow response Chalk Aquifer zone, a fast response zone representing clay areas, and a third zone representing runoff from urban areas, which is the approach that has been adopted in other applications of CATCHMOD [Wilby, 2005]. The model has 15 parameters, of which five parameters are used to represent the runoff response characteristics of each zone. Two parameters are set to zero and 13 need to be calibrated.

Following the approach of Wilby [2005], a Monte Carlo simulation routine was implemented to generate 10,000 parameter sets uniformly sampled from between 0 and 2 times the recommended Environment Agency values shown in Table 5. Parameter sets obtained from each run were used to simulate river flow of the Thames at Kingston using observed daily rainfall and PET for the period 1961–1990. Percent bias (PBIAS) was used to assess the performance of each parameter set. PBIAS is defined as [Gupta *et al.*, 1999]

$$\text{PBIAS} = \left[ \frac{\sum_{i=1}^n (Y_i^{\text{obs}} - Y_i^{\text{sim}})}{\sum_{i=1}^n (Y_i^{\text{obs}})} \times 100 \right] \quad (3)$$

where 0 is the best possible value and where low magnitude values indicate good model performance. Negative values indicate model overestimation and positive values indicate model underestimation [Moriasi *et al.*, 2007]. Parameter sets with a PBIAS value between  $-0.1$  and  $0.1$  over the 1961–1990 period were retained for further analysis.



**Figure 6.** Total annual precipitation generated with the stochastic WG. Shaded areas represent full range of projections; blue and red lines represent 100 realizations from two different vectors of change factors  $c_j$ . Insets illustrate the probability density functions for the two change factors for annual precipitation for the Thames at Kingston.

PBIAS was chosen as a performance measure over more commonly used measures in order to avoid the high flow bias typical of NSE (Nash-Sutcliffe Efficiency) and to give equal weight to high and low flows [Krause *et al.*, 2005]. The PBIAS values were normalized and used to calculate the likelihood weighted uncertainty bounds on the river flow predictions using the procedure described by Freer *et al.* [1996].

Filtering the hydrological model parameter sets on the basis of PBIAS led to the selection of 53 behavioral models out of the 10,000 realizations, noting that all behavioral models also had an NSE coefficient greater than 0.6. The 95% likelihood weighted prediction interval for the simulated flows is shown in Figure 7, together with the observed flows for 1974–1976, including the 1976 drought.

The identifiability of the parameters, in particular of the Potential Drying Constant and of the Nonlinear storage constant, was found to be very low, in agreement with published results [Wilby, 2005]. Wilby [2005] also demonstrates that parameter identifiability is greater for wet than for dry periods in the Thames catchment. Prediction at low flows is sensitive to the Direct Percolation parameter [cf. Cloke *et al.*, 2010].

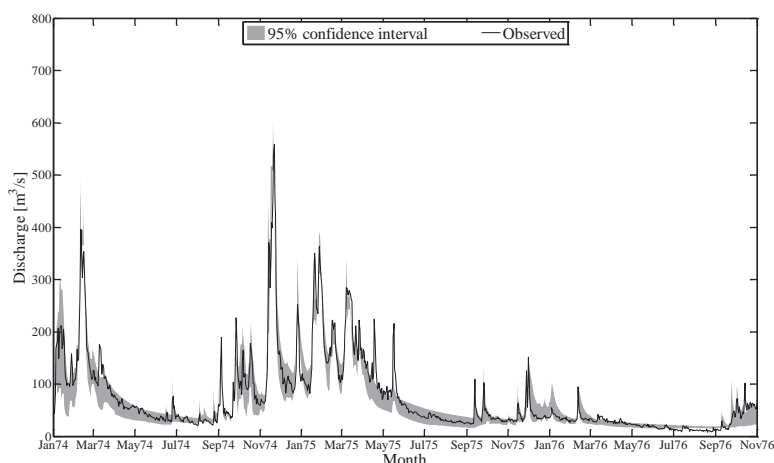
### 3.5. Future River Flow Projections

The ensemble of daily rainfall and PET time series from the WG was run through the behavioral model set to generate river flow projections for the period 1961–2060. River flow projections obtained by running the

WG ensemble through CATCHMOD were compared with the projections for the Thames at Kingston generated by the Future Flows project [Prudhomme *et al.*, 2013]. The Future Flows project produced an ensemble of 11 plausible realizations of future river flows obtained using UKCP09 and several different hydrological models

**Table 5.** CATCHMOD Parameters Used for Simulating Daily Discharge for the Thames at Kingston [Wilby, 2005]

Parameter	Zone 1: Chalk	Zone 2: Clay	Zone 3: Urban
Direct percolation (%)	20	0	0.5
Potential drying constant (mm)	80	100	0
Gradient of the drying curve	0.3	0.3	0.3
Linear storage constant (days)	20	2	0.5
Nonlinear storage constant (days)	300	2	0.25



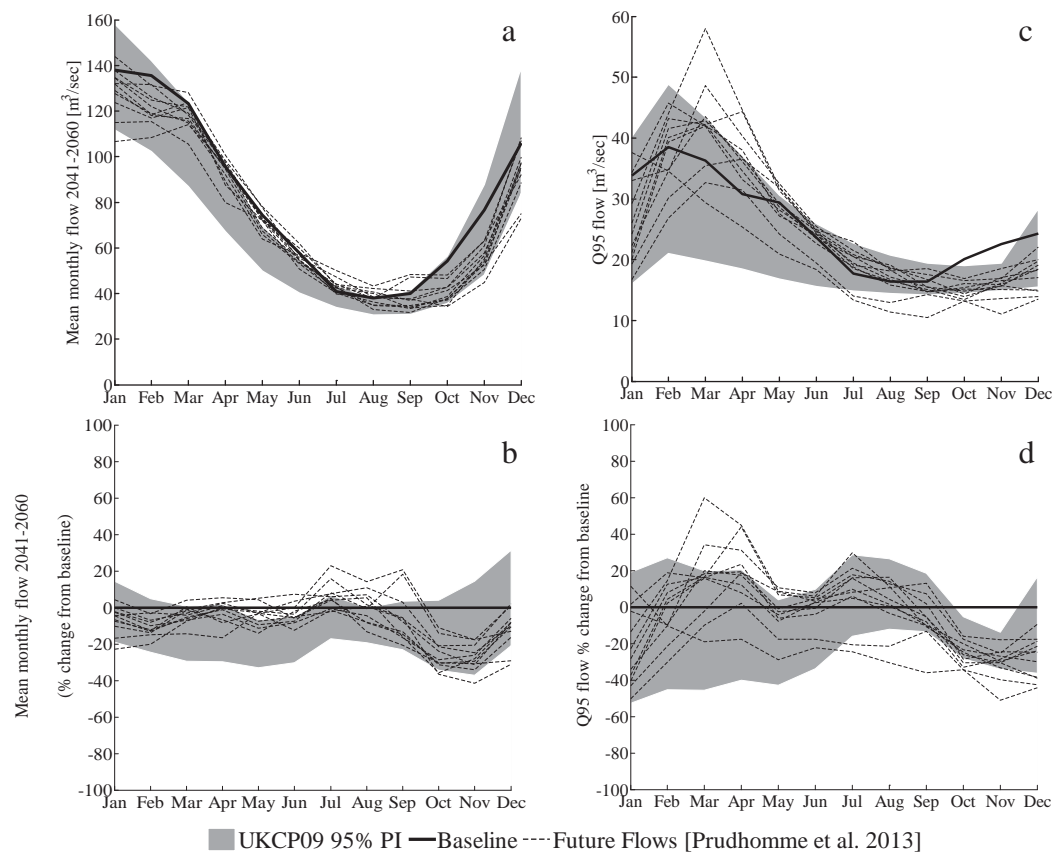
**Figure 7.** Observed daily discharge for the Thames at Kingston and 95% PBIAS weighted confidence interval for 1974–1976. Results show model skill for the calibration period only (1961–1990).

[Prudhomme *et al.*, 2013]. For future climate conditions, the hydrological model parameters were assumed to be independent of climate [cf. Prudhomme and Davies, 2009].

The 10,000 climate projections were run through one behavioral hydrological model to compare UKCP09-based river flow projections with projections generated by the Future Flows project [Prudhomme *et al.*, 2013] and to recognize the contribution of uncertainty in climate projections to flow projection uncertainty. Figure 8a shows the mean monthly flow for the period 2041–2060 obtained by running the UKCP09 10,000 projections through one hydrological model. For mean monthly flows, the UKCP09-CATCHMOD-based projections encompass most of the variability expressed by the Future Flows projections. Figure 8b shows that both projections show significant decreases (–20%) in mean monthly flows for the summer months. Figure 8c shows the projected low flows for the 2041–2060 period for the UKCP09-CATCHMOD ensemble and for the Future Flows ensemble and Figure 8d shows the change with respect to the baseline. Both projections show significant decreases in low summer flows.

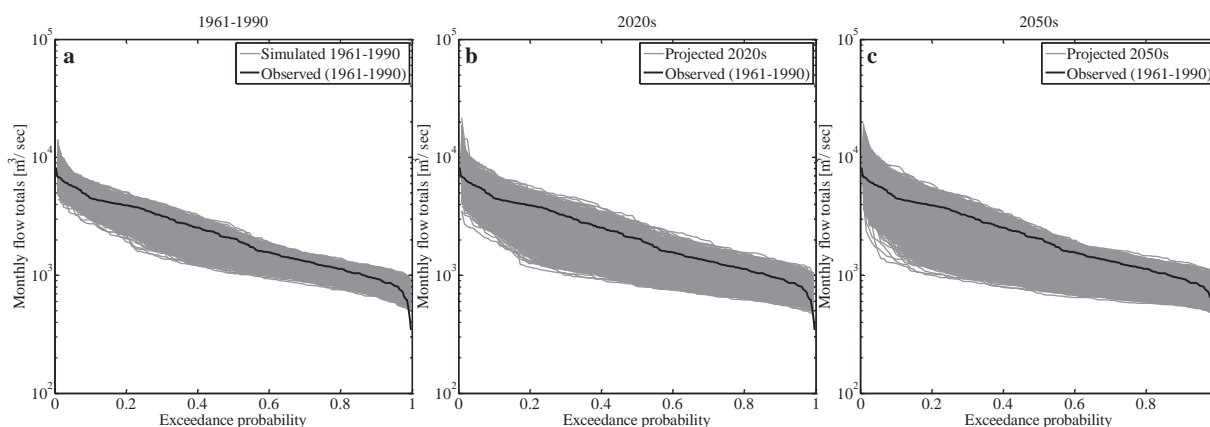
The flow duration curves for the projected flows span a much wider range than the projected flows for the baseline (Figure 9), indicating the greater spread of projections for the future expected given the wide range of rainfall and PET projected by UKCP09. In general, the flow duration curve for the Thames at Kingston has a flat slope suggesting that stream flow in this catchment is heavily sustained by groundwater base flow. The flow duration curves for the 2030s and 2050s show a lower steepness and a flattening at high flows. High flows with exceedance probabilities between 0.1 and 0.4 are projected to be lower than the baseline. The plots in Figure 9 also show that in the future midrange flows (exceedance probability between 0.4 and 0.6) and the median are projected to be lower than the baseline, which could have implications for water resources because this is the range of maximum allowed abstraction.

To understand the relative importance of climate projection uncertainty and hydrological model parameter uncertainty on river flow projections, we employ a simple one-factor-at-a-time approach and compare the projected flows generated by running the full 10,000 climate projections through one hydrological model with the flows generated by running the median future climate projection through the 53 behavioral hydrological models. Figure 10 shows a comparison of the cumulative distributions calculated for different flow statistics for these two cases and also for Future Flows data. The left column shows the projected discharge for each of the three experiments and the right column shows the projected % change in discharge from the baseline. Figure 10a shows that the contribution of climate projection uncertainty (black line) is greater when looking at total annual discharge, because the spread of values projected across the UKCP09 ensemble is much larger than the spread of values and % change from the baseline projected across the 53 behavioral hydrological models (light gray line). Figure 10b shows the cumulative distributions for mean 2041–2060 October discharge and suggests that also for mean monthly discharges the uncertainty coming from the spread in future climate projections is greater than the uncertainty from different hydrological model parameters. At high flows (Q5) the contribution of hydrological model parameter uncertainty is of

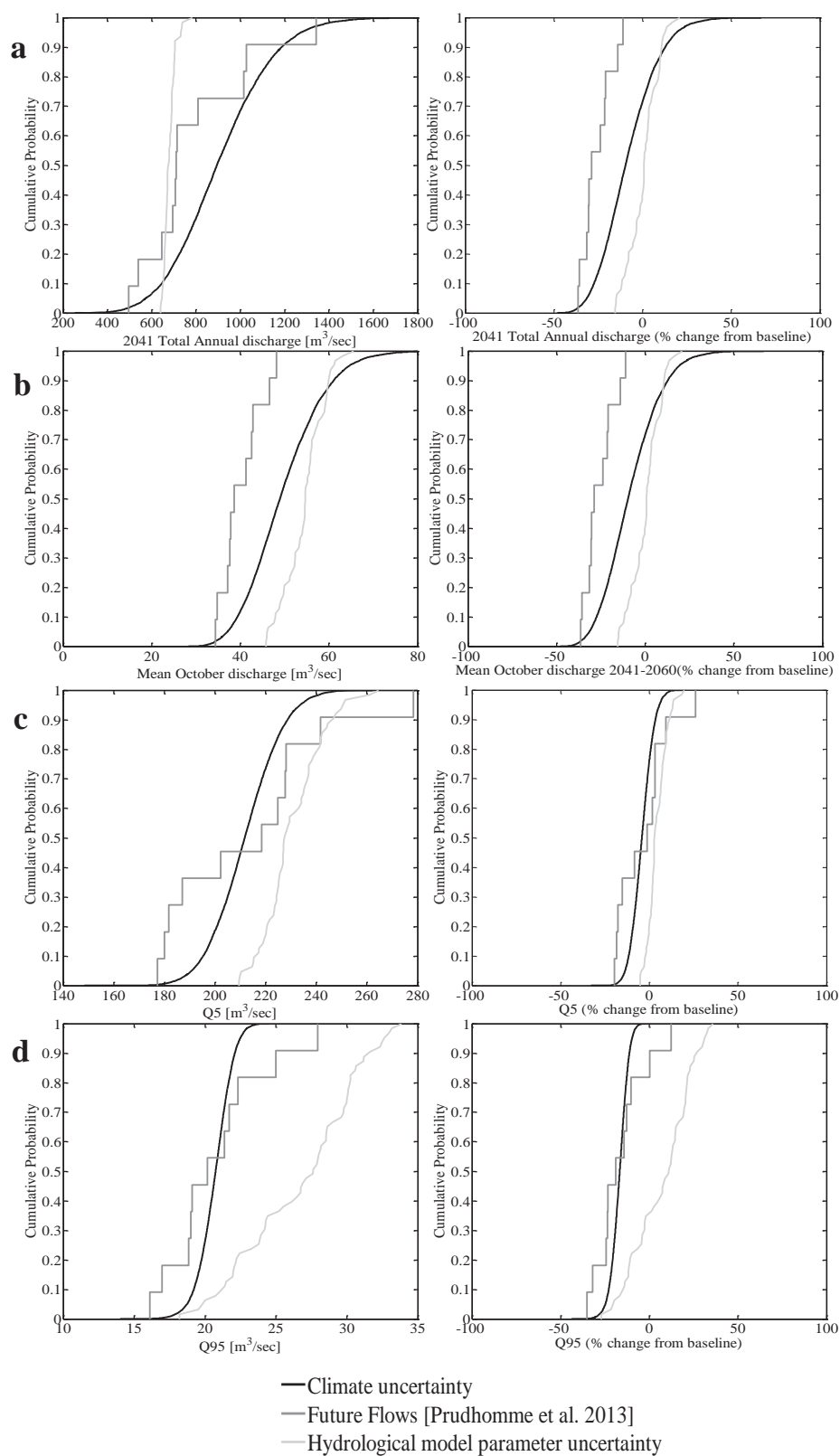


**Figure 8.** (a) Mean monthly flow for the Thames at Kingston for the 2041–2060. (b) Change for 2041–2060 and the baseline (1961–1990) mean monthly discharge for the UKCP09 ensemble 95% prediction interval (PI) and for the future flows ensemble. (c) Low flows (Q95) for the Thames at Kingston for the 2041–2060. (d) Change for 2041–2060 and the baseline (1961–1990) low flows for the UKCP09 ensemble and for the future flows ensemble.

the same magnitude as the contribution of climate change uncertainty and the uncertainty projected in the Future Flows data (Figure 10c). At low flows (Q95), uncertainty due to hydrological model parameter uncertainty (light gray line, Figure 10d) starts to dominate the climate projection uncertainty signal, confirming the difficulties of simulating low flows in a highly regulated river with significant groundwater interaction and when a larger number of hydrological model parameters is affecting the prediction [Bekele-Ayalew, 2008; Bosshard et al., 2013; Cloke et al., 2010]. Using CATCHMOD for the same gauging station, Wilby [2005]



**Figure 9.** Flow duration curves for the observed monthly flow totals of the Thames at Kingston for the baseline (1961–1990): (a) the simulated baseline, (b) the 2020s, and (c) the 2050s.



**Figure 10.** Comparison of climate projection and hydrological model parameter uncertainties. (left) (a) annual discharge, (b) mean October discharge, (c) high flows (Q5), and (d) low flows (Q95) and (right) % change in discharge for the baseline for the same variables.

also finds that uncertainty in flow changes due to model parameter equifinality is higher in winter than in summer and in general that uncertainty in flow changes is greater for wet years.

### 3.6. Water Resources System Model

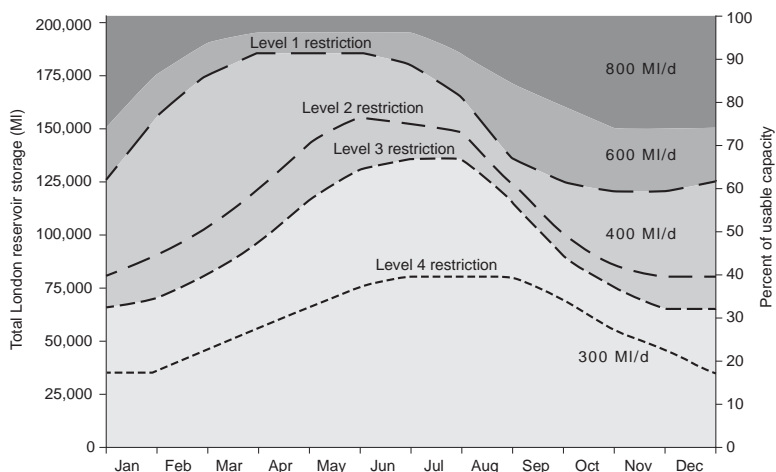
A simplified version of the water supply infrastructure of the London WRZ was represented using IRAS-2010, an open source water resources system model [Matrosov *et al.*, 2011]. IRAS-2010 is a rule-based, computationally efficient water management simulator. Rule-based models have the advantage of reproducing advanced allocation mechanism and of executing instructions sequentially based on logical statements and iterative solution procedures [Matrosov *et al.*, 2011]. In IRAS-2010, the water system is conceptualized as a network of nodes and links. Demand, storage, and inflow points can be represented as nodes. Each demand node will have specified target nodes, for instance storage or inflow points, from which it requests water. Storage curves can be specified to regulate reservoir releases and demand reductions.

In this illustrative representation of the London WRZ, water is supplied by the river Thames at Kingston and by a groundwater source. A single reservoir representing the total storage capacity of London's reservoirs is filled by pumping from the river Thames subject to a maximum allowed abstraction limit [Environment Agency, 2004]. Two strategic supply options, a 150 MI/d desalination plant and a surface water-groundwater conjunctive use scheme, which are activated only when the natural flow in the river is less than 3000 MI/d for 10 consecutive days, are also represented in the model. The river flow time series for the Thames at Kingston presented in section 3.5 are used as inputs to the water resources system model. Yield from groundwater sources, which represent about 20% of the total supply, was assumed to be equal to the dry year deployable output, that is, the maximum rate at which groundwater sources can supply water through a dry period as identified by Thames Water Utilities [Thames Water, 2013].

Water abstracted from the river Thames at Kingston is pumped to a reservoir, representing the total storage capacity for London, which is operated according to the Lower Thames Control Diagram (LTCD). The LTCD regulates abstraction from the river Thames at Kingston subject to minimum downstream target environmental flows and maximum abstraction limits [Thames Water, 2013]. The quantity of water that can be abstracted and therefore the water system's supply capability depend on the storage levels in the reservoir, the need to ensure minimum environmental flows, and the time of the year. As reservoir levels fall, the environmental flows are reduced to a minimum of 300 MI/d, thus allowing for some continued abstraction in all but the most extreme dry periods. At the same time, as storage levels decline, more stringent water use restrictions are applied on demand. In the model, water use restrictions are imposed on demand when reservoir levels fall below storage thresholds defined in the LTCD (Figure 11). The frequency with which restrictions are imposed defines the company's LoS (Table 1).

Demand is modeled using population and per capita consumption data from the water utility company [Thames Water, 2013]. In this case study, demand is assumed to be constant (i.e., no interannual demand profile) and not sensitive to climate change. This assumption is supported by studies of household demand in England, which suggest that household demand is not very sensitive to climate change [Herrington, 1996; HR Wallingford, 2012]. Information on base year population and consumption was obtained from Thames Water Utilities' water resources management plan [Thames Water, 2013]. Population changes over the simulation period were modeled by adopting 0.7% growth per annum and 1% growth per annum scenarios, which result in a 1.3 million people and 2 million people increase by 2040 respectively from 2012 levels, again following the assumptions adopted for planning purposes in the London WRZ.

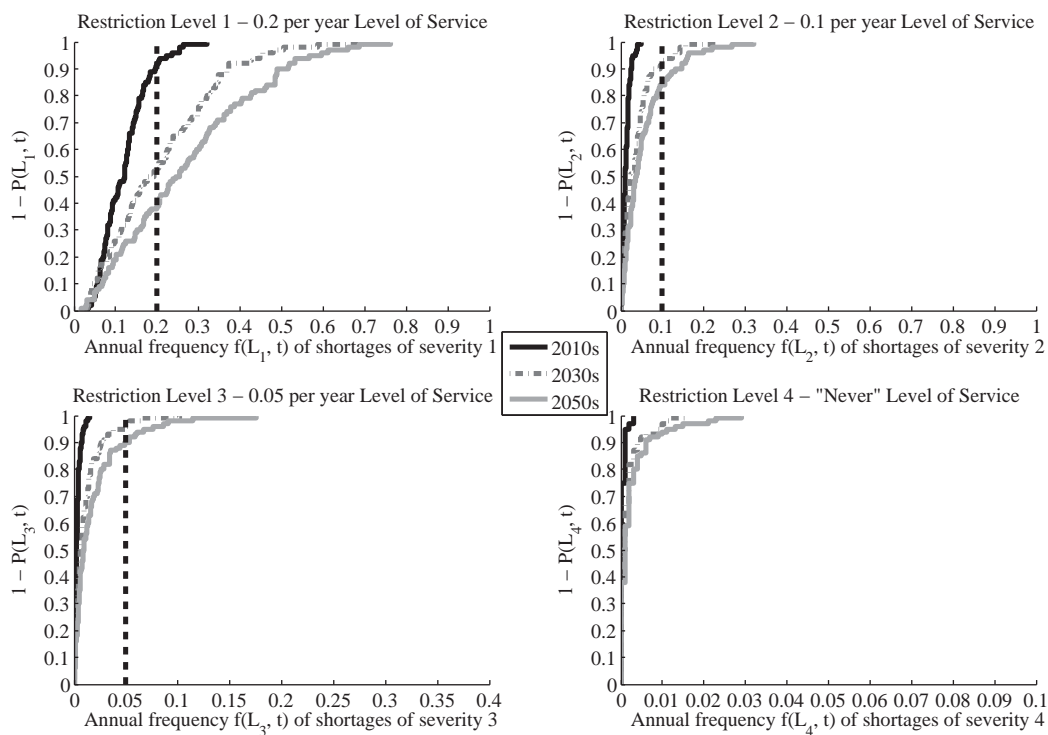
The IRAS-2010 water resources model was run on a weekly time step for the period 2001–2060 with the ensemble of river flow time series generated by forcing each of the 53 behavioral hydrological models with the full 10,000 future climate time series. A water shortage occurs in the model every time reservoir storage falls below the reservoir level thresholds defined in the Lower Thames Control Diagram (Figure 11). When the reservoir level thresholds are breached, the demand reductions shown in Table 1 are applied in the model. Demand reductions are lifted when the storage levels rise above the threshold levels. For each model run, the number of water shortage occurrences of different severity in each year of the simulation was recorded. The passing of these thresholds is associated with a water use restriction, which can be compared with the LoS shown in Table 1.



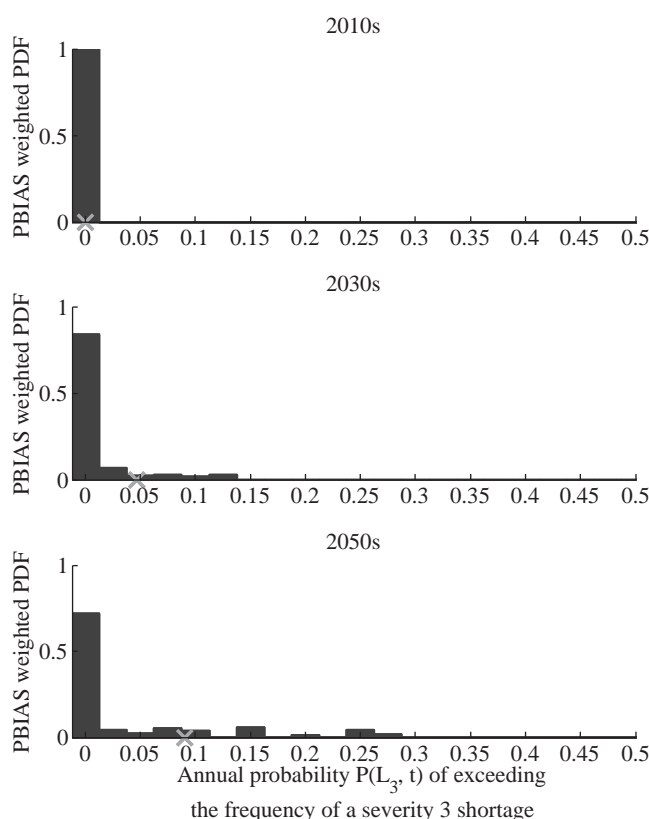
**Figure 11.** Lower Thames Control Diagram showing storage control curves, levels of restriction, and target environmental flow releases.

### 3.7. Estimating the Probability of Failing to Meet Levels of Service Under Climate Change

Figure 12 shows the simulated frequency  $f(L_i, t | z_{hi}, u_w)$  of water shortages for three different decades for one parameterization of the hydrological model and assuming no changes in supply infrastructure or demand (i.e., no population changes from the 2010 baseline, no climate change implication on demand). The vertical lines represent the LoS frequency for each water shortage severity level. No LoS frequency is shown for a severity 4 water shortage because Thames Water Utilities has stated that Level 4 shortages, involving standpipes and rota cuts, should never be required because the consequences of water supply failure would be disastrous for London and the national economy [Thames Water, 2013].



**Figure 12.** Annual frequency of four levels of water shortage for three representative decades based on the 10,000 members UKCP09 ensemble and one parameterization of the hydrological model assuming no changes in supply infrastructure and demand. Vertical dotted lines represent Level of Service frequencies.



**Figure 13.** PBIAS weighted distributions of the annual probability of exceeding the Level of Service frequency of a severity 3 shortage assuming no changes in supply infrastructure and demand. Gray crosses represent results obtained with the CATCHMOD parameters shown in Table 5.

distribution of the probability of exceeding the LoS frequency is then constructed by repeating this procedure for each behavioral parameterization of the hydrological model.

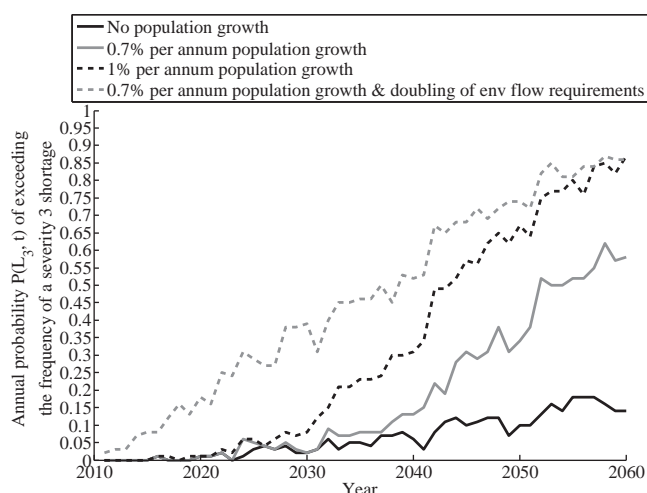
Figure 13 shows the histogram of values of  $P(L_3, t)$  obtained from the 53 behavioral hydrological models. The risk estimates have been weighted using the PBIAS likelihoods. The gray crosses in Figure 13 show the  $P(L_3, t)$  value obtained with the recommended CATCHMOD's parameters shown in Table 5. The effects of hydrological parameter uncertainty on the final risk estimates are shown in Figure 13. Looking into the future, the assessed risk progressively increases across the whole model ensemble. Although the majority of models show a probability of exceeding the LoS frequency smaller than 0.1, the spread in the projected values is significant especially for the 2050s, implying that hydrological model parameter uncertainty has a significant impact on the simulation results, as also highlighted in Figure 10.

### 3.8. Analyzing Sensitivity to Assumptions and Identifying Adaptation Decisions

The impacts that different scenarios on population growth and environmental flow requirements have on the probability of failing to meet the planned LoS are shown in Figure 14. Figure 14 shows the annual probability  $P(L_3, t)$  for one parameterization of the hydrological model. The system shows a fairly low sensitivity to 0.7% per annum population growth through to the 2030s, while the effects of 1% per annum population growth become noticeable sooner. In this latter scenario, the population supplied by the system reaches 11 million people in 2060, leading to a 0.5 probability of failing to meet the required LoS by 2040 if no management actions were to be undertaken. The rate of population growth has a nonlinear effect on the probability of failing to meet LoS.

Results indicate that changes in demand could have greater effects on water supply security than climate change as represented by the UKCP09 projections. The results also illustrate the sensitivity of the system to a doubling of environmental flow requirements (i.e., a doubling of the target environmental flows shown in

For water shortages of severity 1, 2, and 3, the probability of exceeding the LoS frequency  $P(L_i, t)$  can be estimated from the cumulative distribution (shown in Figure 12) by reading off the probability value where the curve intersects the LoS frequency line and by calculating the complement of this value. The probability of exceeding the LoS frequency increases for decades beyond 2010s, reflecting the greater range of projected climate conditions for the future. For this parameterization of the hydrological model, the probability of exceeding the Level 3 LoS (0.05 per year) is 0.03 in the 2030s across the UKCP09 climate projections. In the 2050s, the probability of exceeding the 0.05 per year LoS increases to 0.1. The transient nature of the climate projections allows for the continuous depiction of the time evolution of the assessed risks. The risk metric can be calculated for each year of the simulation period and a



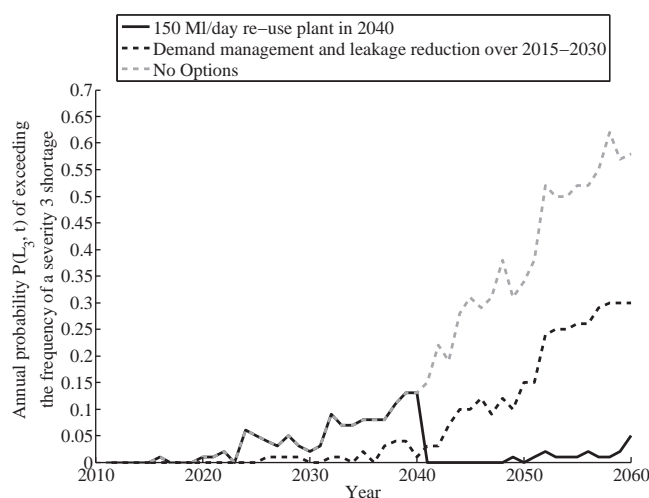
**Figure 14.** Probability  $P(L_3, t)$  of failing to meet a 1 in 20 years Level of Service for a severity 3 water shortage for different population and environmental flow requirements assumptions for one behavioral parameterization of the hydrological model.

Figure 11) paired with a 0.7% per annum population growth scenario. Under this scenario, which was selected for illustrative purposes to show how assumptions about environmental flow requirements can be included in the analysis, there would be a 0.4 probability of failing to meet the LoS frequency in 2030 if no supply or demand management options were to be implemented. Our framework enables visualization and comparison of multiple objectives and trade-offs between different water users, such as domestic water users and the environment.

By visualizing how risks change progressively over time, water

planners are also able to estimate the point in the future when adaptation actions will be required to ensure water supply security. This is particularly important from a water planning perspective given the long lead times required for implementing some large-scale infrastructure options. For instance, Figure 15 shows how under a 0.7% per annum population growth scenario, the implementation of a 150 MI/d reuse plant (black solid line) would be required in 2040 to maintain risks below a 0.15 probability of not meeting the LoS for a Severity 3 shortage.

Demand management options can be similarly tested in our framework. For instance, the water utility in the London WRZ is planning to reduce leakage by approximately 103 MI/d from current levels between 2015 and 2030 and to reduce per capita consumption by installing household water meters, enhancing water efficiency, and promoting behavior change, for an additional 110 MI/d demand reduction over 2015–2030 [Thames Water, 2013]. The leakage and demand reduction plan decreases the risk of failing to meet the planned LoS frequency compared to a do nothing option (black dashed line in Figure 15).



**Figure 15.** Probability  $P(L_3, t)$  of exceeding a 1 in 20 year Level of Service for different adaptation options under a 0.7% per annum population growth scenario for one behavioral parameterization of the hydrological model.

## 4. Discussion

### 4.1. Limitations

The methodology developed in this paper provides a framework for incorporating multiple sources of uncertainty in water resources management decisions. Any methodology, particularly when aimed at informing applied management decisions, involves assumptions and limitations in terms of model choice and incorporation of uncertainties. The proposed approach involves much more extensive sampling of these uncertainties than has hitherto been the case, connecting the results

directly with the risk indicators used in management decisions. Inevitably there are limitations, particularly associated with the representation of future climate and in the way the catchment is modeled.

The UKCP09 projections used in this study are arguably the most sophisticated probabilistic climate change information available. However, they reflect the limitations of the underlying global and regional climate models, in particular in their representation of extremes and climatic processes of relevance to water resources (e.g., atmospheric blocking and the jet stream).

Although widely used in climate impact assessment studies [e.g., *Diaz-Nieto and Wilby*, 2005; *Arnell*, 2003; *Prudhomme et al.*, 2010], change factor approaches have well-known limitations [*Wilby et al.*, 2004]. Change factors implicitly correct for bias in the climate model representation of baseline climatology. On the one hand, this is desirable, because at a regional scale most climate models contain significant biases, especially in precipitation. However, the correction for this bias can suppress climate model uncertainties. In the approach adopted here, change factors have been used alongside an extensive sampling of climate model uncertainties, which to some extent addresses this limitation. There are also methodological choices in the use of additive or multiplicative change factors, and whether to apply changes to native or transformed scales. The choices that have been applied in the UKCP09 WG are discussed by *Jones et al.* [2009].

The UKCP09 scenarios project changes to the seasonality of UK precipitation, generally toward wetter winters and drier summers, which is reflected in the WG outputs. Precipitation in the Thames catchment does not show any significant interannual autocorrelation, so UKCP09 produces statistically independent successive years. The Thames water resources system is sensitive to multiyear droughts, but in the historic record and in our projections these occur no more frequently than would be expected under the assumption of independent precipitation annual totals given the change factor perturbations [*Hall et al.*, 2012]. Runoff in the Thames catchment is not very sensitive to long-term climate anomalies. *Hannaford et al.* [2005] and *Hannaford and Marsh* [2006] examined the association between runoff and NAO in several undisturbed UK catchments and found weak to no correlations between NAO phases and runoff in the southern regions of the UK, where the Thames catchment is located.

It is not clear whether or not climate change will bring about an increase in drought frequency or persistence [*Watts et al.*, 2014; *Trenberth et al.*, 2013]. For the UK, *Burke and Brown* [2010] have shown that changes in regional drought patterns projected by the Hadley Centre climate model (HadRM3) are not distinguishable from natural variability and projection uncertainty, while work on six UK catchments by *Chun et al.*, [2013] suggests that climate change may cause a change in drought patterns. Other studies suggest an increase in frequency [*Burke et al.*, 2010] and spatial coherence [*Rahiz and New*, 2013] of droughts in the UK. However, they also acknowledge that the uncertainty around changes in drought patterns is significant. Our case study is based on the same Hadley Centre ensemble that was studied by *Rahiz and New* [2013] and *Burke and Brown* [2010]. The WG simulations thus reflect the changes in projected drought frequency, which are most strongly driven by trends of increasing PET. At the scale of this study, the increasing spatial coherence that *Rahiz and New* [2013] identified at a national scale is not relevant. We note that if the method were to be applied in locations that show significant interannual autocorrelation and persistence, then the climate series would need to reflect that. Given that climate models may not accurately reproduce persistence [*Rocheta et al.*, 2014], climate sequences for these locations can be obtained using weather generators such as the one proposed by *Steinschneider and Brown* [2013], where the persistence of annual precipitation can be parametrically adjusted. The flexibility of the methodology means that new climate projections or stochastically generated time series with varying levels of interannual variability can be readily incorporated as they become available.

We recognize that the GCMs underlying the UKCP09 projections do not include important earth system processes (e.g., climate-induced emissions from wetlands, methane hydrates), have uncertainties around parameter values and emission trajectories, and have weaknesses in their representation of salient climatic phenomena, such as atmospheric blocking [*Scaife et al.*, 2010]. Furthermore, we recognize that other approaches exist to estimate climate model structural uncertainty [e.g., *Woldemeskel et al.*, 2012] which go beyond the multimodel ensemble approach used in UKCP09. These limitations emphasize the importance of the extensive sampling of the full range of uncertainties and the need for decision-making frameworks, such as the one proposed here, where all assumptions can be explicitly stated and where sensitivity to these assumptions can be explored in terms of decision-relevant risk metrics.

In the hydrological modeling for the case study, the parameterization of the hydrological model means that changes in land use, vegetation cover, and catchment response are ignored. Given the focus of this study, this was a reasonable assumption, but our risk-based approach allows for the incorporation of future land use scenarios in a suitable hydrological model, such as those developed by *Whitehead et al.* [2013] for the Thames catchment, and the testing of their impacts in terms of increasing or reducing the probability of exceeding a planned LoS. The output from groundwater sources has been taken as being constant throughout the simulation, an assumption that needs to be tested with an improved water system model capable of resolving groundwater storage and transport. In the case study, we tested only a few supply-side and demand-side management actions, but more elaborate simulations might be envisaged including for instance water trading with neighboring water utilities and water quality modeling to estimate risks related to harmful water quality.

#### 4.2. Adaptation Planning Under Climate Change Uncertainty

The methodology presented here is designed to support water resources management and planning under climate change. Other decision-making frameworks have been developed to help water managers deal with severe uncertainties, identify climate risks and vulnerabilities and adaptation options. For example, *Brown et al.* [2012] proposed a methodology called “decision scaling,” which starts by identifying decision thresholds linked to system vulnerabilities and then constructs a climate response function, which links climate conditions to system vulnerabilities. *Nazemi et al.* [2013] explored the impacts of climate change on water resources systems without using information from climate models. They use a two parameter representation of change in river flow regime and visualize system vulnerability to potential variations in these parameters. A similar scenario-neutral approach was presented by *Prudhomme et al.* [2010] to assess the implications of climate change on pluvial flood risk in the UK.

These decision-analytic approaches use climate model information in the latter stages of the impact analysis or do not use it at all, with the objective of testing the sensitivity of water systems to potential future changes rather than seeking to quantify potential impacts. An emphasis on structured sensitivity analysis is also implicit in Info-Gap theory [*Ben-Haim*, 2006; *Korteling et al.*, 2013; *Matrosov et al.*, 2013] and Robust Decision Making (RDM) [*Lempert et al.*, 2006; *Lempert and Groves*, 2010]. Both RDM and Info-Gap Theory are methodologies for exploring decision robustness to severe uncertainty. However, the implementation of these approaches in adaptation planning is challenging because it requires decision makers to decide on the level of robustness and to trade this off with the costs associated with providing robustness, without explicitly stating their attitudes toward risk. In this paper, we have shown that risk-based methods provide a way of explicitly weighing up the risks and costs of each management action, of deciding on the level of adaptation proportionate to the risks [*Hall et al.*, 2013], and of testing the sensitivity of the chosen management actions to assumptions.

While the risk-based approach presented here provides a transparent structuring of all available evidence into a coherent framework, its application remains challenging because tolerable risk thresholds might evolve in the future, depending, in part, on how severe future risks prove to be, on how these risks compare with the costs of adaptation and on how future societal values change the tolerance for water use restrictions [*Wade et al.*, 2013]. This is particularly true when valuing environmental goods and water users’ preferences in the context of long-term changes. However, while we recognize that future preferences are expected to change, the aim of the analysis is to inform investment plans and commitments being made now. So even though these are long-term plans, it is reasonable to base them on today’s preferences.

#### 5. Conclusions

This paper has formulated and demonstrated with an illustrative case study a methodology for using nonstationary probabilistic climate projections to inform risk-based water resources management decisions. The risk-based methodology presented here is useful to decision makers because it provides a coherent approach for incorporating new probabilistic information on climate uncertainty into a decision-making process to evaluate the risk of water shortages. Traditional water planning focuses the water planner’s attention on setting supply-demand balance targets for the future, whereas our approach shifts the focus onto observable outcomes of concern to water users and their probability of occurrence.

Although potentially appealing from the planner's point of view [Pittock *et al.*, 2001], a probabilistic representation of climate uncertainties can lead to the underestimation of future risks and to adaptation decisions which may be vulnerable to these uncertainties [Hall, 2007]. We have shown how our risk-based methodology provides a way to deal with this limitation and test the system's sensitivity to residual uncertainties and assumptions. Furthermore, we have shown that probability concepts can help water planners identify which sources of uncertainties are likely to have the greatest impacts on long-term planning and the degree to which they will influence the probability of undesirable outcomes.

The application of the methodology to the London water resource zone (UK) demonstrated that without further supply or demand interventions, the combined effects of climate change and population growth are projected to increase the probability of exceeding the planned LoS for water shortages to customers. The results indicate that hydrological model parameter uncertainty has a significant impact on the simulation results and that the effects of increasing demand (due to population growth and in the absence of further efforts to limit per capita consumption) are projected to have a greater impact on the frequency of water shortages than climate change. Demand management could go some way in reducing this risk, but the need for major supply-side interventions increases in future.

The framework presented here involves a large number of simulations of plausible futures so its implementation is computationally demanding. Planned investments in the water sector in response to climate change are going to be significant, justifying the need for extensive simulation studies aimed at identifying adaptation strategies. This methodology provides a route to transparently structure all the available evidence and compare between different water management actions in a way that is directly relevant to decision makers.

## References

- Arnell, N. (2003), Relative effects of multi-decadal climatic variability and changes in the mean and variability of climate due to global warming: Future streamflows in Britain, *J. Hydrol.*, 270(3–4), 195–213.
- Bekele-Ayalew, T. (2008), Analyzing uncertainties in water resources projections for the Thames catchment under climate change scenarios, Master of Science in hydro-informatics and water management thesis, Univ. of Newcastle, Newcastle, U. K.
- Ben-Haim, Y. (2006), *Info-Gap Decision Theory: Decisions Under Severe Uncertainty*, 2nd ed., Academic, London, U. K.
- Beven, K. J., and A. M. Binley (1992), The future of distributed models: Model calibration and uncertainty prediction, *Hydrol. Processes*, 6, 279–298.
- Bosshard, T., M. Carambia, K. Goergen, S. Kotlarski, P. Krahe, M. Zappa, and C. Schär (2013), Quantifying uncertainty sources in an ensemble of hydrological climate-impact projections, *Water Resour. Res.*, 49, 1523–1536, doi:10.1029/2011WR011533.
- Brekke, L. D., E. P. Maurer, J. D. Anderson, M. D. Dettinger, E. S. Townsley, A. Harrison, and T. Pruitt (2009), Assessing reservoir operations risk under climate change, *Water Resour. Res.*, 45, W04411, doi:10.1029/2008WR006941.
- Brown, C. (2010), The end of reliability [Editorial], *J. Water Resour. Plann. Manage.*, 136(2), 143–145.
- Brown, C., and R. Wilby (2012), An alternate approach to assessing climate risks, *Eos Trans. AGU*, 93(5), 52–53.
- Brown, C., et al. (2010), *Managing Climate Risk in Water Supply Systems*, 133 pp., Int. Res. Inst. for Clim. and Soc., Palisades, N. Y.
- 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.
- Burke, E., and S. J. Brown (2010), Regional drought over the UK and changes in the future, *J. Hydrol.*, 394, 471–485.
- Burke, E., R. Perry, and S. Brown (2010), An extreme value analysis of UK drought and projections of change in the future, *J. Hydrol.*, 388(1–2), 131–143.
- Christerson, B. v., J.-P. Vidal, and S. D. Wade (2012), Using UKCP09 probabilistic climate information for UK water resource planning, *J. Hydrol.*, 424–425, 48–67, doi:10.1016/j.jhydrol.2011.12.020.
- Christensen, N. S., and D. P. Lettenmaier (2007), A multimodel ensemble approach to assessment of climate change impacts on the hydrology and water resources of the Colorado River Basin, *Hydrol. Earth Syst. Sci.*, 11, 1417–1434.
- Chun, K. P., H. Wheeler, and C. Onof (2013), Prediction of the impact of climate change on drought: An evaluation of six UK catchments using two stochastic approaches, *Hydrol. Processes*, 27(11), 1600–1614, doi:10.1002/hyp.9259.
- Cloke, H. L., C. Jeffers, F. Wetterhall, T. Byrne, J. Lowe, and F. Pappenberger (2010), Climate impacts on river flow: Projections for the Medway catchment, UK, with UKCP09 and CATCHMOD, *Hydrol. Processes*, 24(24), 3476–3489, doi:10.1002/hyp.7769.
- 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, doi:10.1007/s10584-005-1157-6.
- Environment Agency (2004), *Thames Corridor. Abstraction Management Strategy*, Environ. Agency, Bristol, U. K.
- Environment Agency (2008), *Water Resources in England and Wales—Current State and Future Pressures*, Environ. Agency, Bristol, U. K.
- Environment Agency (2012), *Water Resources Planning Guideline*, Environ. Agency, Bristol, U. K.
- Freer, J., K. Beven, and B. Ambrose (1996), Bayesian estimation of uncertainty in runoff prediction and the value of data: An application of the GLUE approach, *Water Resour. Res.*, 32(7), 2161–2173, doi:10.1029/95WR03723.
- Fung, F., G. Watts, A. Lopez, H. Orr, M. New, and C. Extence (2013), Using large climate ensembles to plan for the hydrological impact of climate change in the freshwater environment, *Water Resour. Manage.*, 27(4), 1063–1084, doi:10.1007/s11269-012-0080-7.
- Groves, D. G., D. Knopman, R. J. Lempert, S. H. Berry, and L. Wainfan (2008a), *Presenting Uncertainty About Climate Change to Water-Resource Managers: A Summary of Workshops with the Inland Empire Utilities Agency*, RAND Corp., Santa Monica, Calif.
- Groves, D. G., D. Yates, and C. Tebaldi (2008b), Developing and applying uncertain global climate change projections for regional water management planning, *Water Resour. Res.*, 44, W12413, doi:10.1029/2008WR006964.

## Acknowledgments

Edoardo Borgomeo is funded by the Engineering and Physical Sciences Research Council, the Environment Agency (science project SC120053) and Thames Water. This work has also been supported by the Natural Environment Research Council under grant NE/J017302/1: Consortium on Risk in the Environment: Diagnostics, Integration, Benchmarking, Learning and Elicitation (CREDIBLE). We thank the associate editor and three anonymous reviewers for their helpful criticism and comments that helped to improve the article. We thank Evgenii Matrosov for his advice on using IRAS-2010, Vassilis Glenis and Lucy Manning for their help in retrieving the PET data and Ailsa Allen for drawing Figure 11. The views expressed in the paper reflect those of the authors and are not indicative of the positions held by the Environment Agency and Thames Water. Data: Historical rainfall and evaporation data for the Thames basin can be requested from the UK Met Office Integrated Data Archive System (MIDAS) database ([http://badc.nerc.ac.uk/view/badc.nerc.ac.uk\\_\\_ATOM\\_\\_ACTIVITY\\_e8419d56-d731-11e1-b5aa-00163e251233](http://badc.nerc.ac.uk/view/badc.nerc.ac.uk__ATOM__ACTIVITY_e8419d56-d731-11e1-b5aa-00163e251233)) and the Met Office MORECS system respectively. Historical river flow data and synthetic stream flows from the Future Flows project for the Thames at Kingston can be found in the National River Flow Archive's database (<http://www.ceh.ac.uk/data/nrfa/index.html>). Transient WG data can be obtained from the corresponding author. Data on London water system's characteristics, including water use and reservoir operations, can be found in Thames Water's Water Management Plan [Thames Water, 2013]. IRAS-2010 is a freely available open source modeling platform (<https://code.google.com/p/iras/downloads/list>). Details on CATCHMOD can be found in Wilby *et al.* [1994].

- Gupta, H., S. Sorooshian, and P. O. Yapo (1999), Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration, *J. Hydrol. Eng.*, 4(2), 81–103.
- Hall, J. (2007), Probabilistic climate scenarios may misrepresent uncertainty and lead to bad adaptation decisions, *Hydrol. Processes*, 21(8), 1127–1129, doi:10.1002/hyp.6573.
- Hall, J. W., G. Watts, M. Keil, L. de Vial, R. Street, K. Conlan, P. E. O’Connell, K. Beven, and C. G. Kilsby (2012), Towards risk-based water resources planning in England and Wales under a changing climate, *Water Environ. J.*, 26(1), 118–129, doi:10.1111/j.1747–6593.2011.00271.x.
- Hall, J. W., S. Brown, R. J. Nicholls, N. F. Pidgeon, and R. T. Watson (2013), Proportionate adaptation, *Nat. Clim. Change*, 2, 833–834.
- Hannaford, J., and T. Marsh (2006), An assessment of trends in UK runoff and low flows using a network of undisturbed catchments, *Int. J. Climatol.*, 26, 1237–1253.
- Hannaford, J., C. L. R. Laize, and T. J. Marsh (2005), An assessment of runoff trends in natural catchments in the celtic regions of North West Europe, in *Proceedings of the Fourth Inter-Celtic Colloquium on Hydrology and Management of Water Resources*, edited by J. P. Lobo Ferreira and J. M. P. Vieira, Assoc. Port. dos Recursos Hidricos, Lisbon, p. 78–85.
- 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(256), 56–66.
- Herrington, P. (1996), *Climate Change and the Demand for Water*, 164 pp., H.M. Stn. Off., London, U. K.
- Hirsch, R. M. (1978), Risk analyses for a water supply system: Occoquan Reservoir, Fairfax and Prince William Counties, Virginia, USA, *Hydrol. Sci. Bull.*, 23(4), 475–505.
- Horton, P., B. Schaeffli, A. Mezghani, B. Hingray, and A. Musy (2006), Assessment of climate-change impacts on alpine discharge regimes with climate model uncertainty, *Hydrol. Processes*, 20(10), 2091–2109, doi:10.1002/hyp.6197.
- HR Wallingford (2012), Thames water climate change impacts on demand for the 2030s, *Rep. EX6828*, Wallingford, U. K.
- Jones, P. D., C. G. Kilsby, C. Harpham, V. Glenis, and A. Burton (2009), UK Climate Projections Science Report: Projections of Future Daily Climate for the UK from the Weather Generator, Univ. of Newcastle, Newcastle, U. K.
- Kilsby, C. G., P. D. Jones, A. Burton, A. C. Ford, H. J. Fowler, C. Harpham, P. James, A. Smith, and R. L. Wilby (2007), A daily weather generator for use in climate change studies, *Environ. Modell. Software*, 22(12), 1705–1719, doi:10.1016/j.envsoft.2007.02.005.
- 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.
- Krause, P. B., D. P. Boyle, and F. Base (2005), Comparison of different efficiency criteria for hydrological model assessment, *Adv. Geosci.*, 5, 89–97.
- Kundzewicz, Z. W., L. J. Mata, N. W. Arnell, P. Döll, B. Jimenez, K. Miller, T. Oki, Z. Sen, and I. Shiklomanov (2008), The implications of projected climate change for freshwater resources and their management, *Hydrol. Sci. J.*, 53(1), 3–10, doi:10.1623/hysj.53.1.3.
- Lempert, R., D. G. Groves, S. Popper, and S. Banks (2006), A general, analytic method for generating robust strategies and narrative scenarios, *Manage. Sci.*, 52(4), 514–528.
- Lempert, R. J., and D. G. Groves (2010), Identifying and evaluating robust adaptive policy responses to climate change for water management agencies in the American west, *Technol. Forecasting Soc. Change*, 77(6), 960–974, doi:10.1016/j.techfore.2010.04.007.
- 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.
- 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(4), 87–93, doi:10.1002/wea.67.
- Matrosov, E. S., J. J. Harou, and D. P. Loucks (2011), A computationally efficient open-source water resource system simulator—Application to London and the Thames Basin, *Environ. Modell. Software*, 26(12), 1599–1610, doi:10.1016/j.envsoft.2011.07.013.
- Matrosov, E. S., A. M. Woods, and J. Harou (2013) Robust Decision Making and Info-Gap Decision Theory for water resources system planning, *J. Hydrol.*, 494, 43–58.
- McIntyre, N., M. Lees, H. S. Wheeler, C. Onof, and B. J. Connorton (2003a), Evaluation and visualisation of risk to water resources, *Proc. ICE Water Mar. Eng.*, 156(1), 1–11.
- McIntyre, N., T. Wagener, H. S. Wheeler, and S. C. Chapra (2003b), Risk-based modelling of surface water quality: A case study of the Charles River, Massachusetts, *J. Hydrol.*, 274(1–4), 225–247, doi:10.1016/S0022–1694(02)00417–1.
- Milly, P. C. D., J. Betancourt, M. Falkenmark, R. M. Hirsch, Z. W. Kundzewicz, D. P. Lettenmaier, and R. J. Stouffer (2008), Stationarity is dead: Whither water management?, *Science*, 319(5863), 573–574, doi:10.1126/science.1151915.
- Montanari, A., and A. Brath (2004), A stochastic approach for assessing the uncertainty of rainfall-runoff simulations, *Water Resour. Res.*, 40, W01106, doi:10.1029/2003WR002540.
- Moriasi, D. N., J. G. Arnold, M. W. Van Liew, R. L. Bingner, R. D. Harmel, and T. L. Veith (2007), Model evaluation guidelines for systematic quantification of accuracy in watershed simulations, *Trans. Am. Soc. Agric. Biol. Eng.*, 50(3), 885–900.
- Murphy, J. M., B. Booth, M. Collins, G. R. Harris, D. 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, 1993–2028.
- Murphy, J. M., D. Sexton, G. Jenkins, P. Boorman, B. Booth, C. Brown, R. Clark, M. Collins, G. Harris, and L. Kendon (2009), *UK Climate Projections Science Report: Climate Change Projections*, Met. Off. Hadley Cent., Exeter, U. K.
- Nardini, A., C. Piccardi, and R. Soncini-Sessa (1992), On the integration of risk aversion and average-performance optimization in reservoir control, *Water Resour. Res.*, 28(2), 487–497, doi:10.1029/91WR02394.
- 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, doi:10.1098/rsta.2007.2080.
- Perry, M. (2006), A spatial analysis of trends in the UK climate since 1914 using gridded datasets, *Natl. Clim. Inf. Cent. Clim. Memo.* 21, MetOffice, Exeter, U. K.
- Pittock, A. B., R. Jones, and C. Mitchell (2001), Probabilities will help us plan for climate change, *Nature*, 413(6853), 249.
- Prudhomme, C., and H. Davies (2009), Assessing uncertainties in climate change impact analyses on the river flow regimes in the UK. Part 2: Future climate, *Clim. Change*, 93(1–2), 197–222, doi:10.1007/s10584-008-9461-6.
- Prudhomme, C., R. L. Wilby, S. Crooks, A. L. Kay, and N. S. Reynard (2010), Scenario-neutral approach to climate change impact studies: Application to flood risk, *J. Hydrol.*, 390(3–4), 198–209, doi:10.1016/j.jhydrol.2010.06.043.

- Prudhomme, C., et al. (2013), Future flows hydrology: An ensemble of daily river flow and monthly groundwater levels for use for climate change impact assessment across Great Britain, *Earth Syst. Sci. Data*, 5(1), 101–107.
- Rahiz, M., and M. New (2013), 21st century drought scenarios for the UK, *Water Resour. Manage.*, 27(4), 1039–1061.
- 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.
- Scaife, A. A., T. Woolings, J. Knight, G. Martin, and T. Hinton (2010), Atmospheric blocking and mean biases in climate models, *J. Clim.*, 23(23), 6143–6152.
- Sexton, D. M., J. M. Murphy, M. Collins, and M. J. Webb (2012), Multivariate probabilistic projections using imperfect climate models part I: Outline of methodology, *Clim. Dyn.*, 38(11–12), 2513–2542.
- Simonovic, S. P., H. D. Venema, and D. H. Burn (1992), Risk-based parameter selection for short-term reservoir operation, *J. Hydrol.*, 131(1–4), 269–291, doi:10.1016/0022-1694(92)90222-H.
- 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(1857), 2145–2161, doi:10.1098/rsta.2007.2074.
- 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, 1–17, doi:10.1002/wrcr.20528.
- Tebaldi, C., and R. Knutti (2007), The use of the multi-model ensemble in probabilistic climate projections, *Philos. Trans. R. Soc. A*, 365, 2053–2075.
- Tebaldi, C., D. Smith, D. Nychka, and L. O. Mearns (2005), Quantifying uncertainty in projections of regional climate change: A Bayesian approach to the analysis of multimodel ensembles, *J. Clim.*, 18(10), 1524–1540.
- Thames Water (2013), *Water Resources Management Plan 2015–2040*, Thames Water Utilities Ltd., Reading, U. K.
- Trenberth, K. E., A. Dai, G. van der Schrier, P. D. Jones, J. Barichivich, K. R. Briffa, and J. Sheffield (2013), Global warming and changes in drought, *Nat. Clim. Change*, 4, 17–22.
- Turner, S. W., D. Marlow, M. Ekstrom, 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 (2012), Water resources planning tools 2012. Definitions, *Rep. Ref No. 12/WR/27/6*, U. K. Water Ind. Res., London, U. K.
- Vörösmarty, C. J., P. Green, J. Salisbury, and R. B. Lammers (2000), Global water resources: Vulnerability from climate change and population growth, *Science*, 289(5477), 284–288, doi:10.1126/science.289.5477.284.
- Vrugt, J. A., H. V. Gupta, W. Bouten, and S. Sorooshian (2003), A Shuffled Complex Evolution Metropolis algorithm for optimization and uncertainty assessment of hydrologic model parameters, *Water Resour. Res.*, 39(8), 1201, doi:10.1029/2002WR001642.
- Wade, S. D., 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(4), 1085–1109.
- Wagner, J., U. Shamir, and D. Marks (1988), Water distribution reliability: Simulation methods, *J. Water Resour. Plann. Manage.*, 114(3), 276–294.
- Watts G., et al. (2014), Climate change and water in the UK—Past changes and future prospects, *Prog. Phys. Geogr.*, in press.
- Whitehead, P. G., J. Crossman, B. B. Balana, M. N. Futter, S. Comber, L. Jin, D. Skuras, A. J. Wade, M. J. Bowes, and D. S. Read (2013), A cost effectiveness analysis of water security and water quality: Impacts of climate and land use change on the River Thames System, *Philos. Trans. R. Soc. A*, 371, 1–16.
- Wilby, R., B. Greenfield, and C. Glenney (1994), A coupled synoptic-hydrological model for climate change impact assessment, *J. Hydrol.*, 153(1–4), 265–290, doi:10.1016/0022-1694(94)90195-3.
- Wilby, R. L. (2005), Uncertainty in water resource model parameters used for climate change impact assessment, *Hydrol. Processes*, 19(16), 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., S. P. Charles, E. Zorita, B. Timbal, P. Whetton, and L. O. Mearns (2004), *Guidelines for Use of Climate Scenarios Developed from Statistical Downscaling Methods*. IPCC Task Group on Scenarios for Climate Impact Assessment (TGICIA), Geneva, Switzerland. [Available at <http://www.narccap.ucar.edu/doc/tgic-guidance-2004.pdf>.]
- 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.
- Willis, K. G., R. Scarpa, and M. Acutt (2005), Assessing water company customer preferences and willingness to pay for service improvements: A stated choice analysis, *Water Resour. Res.*, 41, W02019, doi:10.1029/2004WR003277.
- Woldemeskel, F. M., A. Sharma, B. Sivakumar, and R. Mehrotra (2012), An error estimation method for precipitation and temperature projections for future climates, *J. Geophys. Res.*, 117, doi:10.1029/2012JD018062.