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Key Points:
- Proposes an integrated water quality-quantity model,including abstraction rules and reservoir water quality,for PWS reliability assessment
- Assesses the impact of land-use change, and potential mitigations, on water supply reliability
- Applies a novel climate dataset to explore hydrological variability and change

Supporting Information:
- Tables S1

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Assessment of Risks to Public Water Supply From Low Flows and Harmful Water Quality in a Changing Climate

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Abstract Water resources planning and management by water utilities have traditionally been based on consideration of water availability. However, the reliability of public water supplies can also be influenced by the quality of water bodies. In this study, we proposed a framework that integrates the analysis of risks of inadequate water quality and risks of insufficient water availability. We have developed a coupled modeling system that combines hydrological modeling of river water quantity and quality, rules for water withdrawals from rivers into storage reservoirs, and dynamical simulation of harmful algal blooms in storage reservoirs. We use this framework to assess the impact of climate change, demand growth, and land-use change on the reliability of public water supplies. The proposed method is tested on the River Thames catchment in the south of England. The results show that alongside the well-known risks of rising water demand in the south of England and uncertain impacts of climate change, diffuse pollution from agriculture and effluent from upstream waste water treatment works potentially represent a threat to the reliability of public water supplies in London. We quantify the steps that could be taken to ameliorate these threats, though even a vigorous pollution-prevention strategy would not be sufficient to offset the projected effects of climate change on water quality and the reliability of public water supplies. The proposed method can help water utilities to recognize their system vulnerability and evaluate the potential solutions to achieve more reliable water supplies.

1. Introduction

The reliability of public water supplies not only depends upon water availability but also upon its quality. In many countries, it is mandatory for water utilities to treat and supply water to specific water quality standards. If the quality of water bodies, such as rivers, reservoirs, or groundwater sources, is poor, then the water companies might decide not to withdraw water from these sources, even if it is needed, as either the water cannot be adequately purified by the treatment works or the treatment cost would be excessively high. Water quality is also a concern for other abstractors, including thermoelectric power plants, where high algal concentrations can lead to cooling plant malfunction, and agricultural abstractors for whom high salinity inhibits plant growth.

Most past studies have considered water quality or water quantity issues separately, but there is a growing literature of coupled studies. Yuan et al. (2015) developed a water quantity and quality joint-operation model of dams and floodgates, where the aim of their model was to find a balance between flood control and pollution prevention. Paredes-Arquiola et al. (2010) examined both water quality and quantity in a river basin and investigated how water quality in the river may change if the water allocations or reservoirs operation change. They also tested alternative future plans, such as the upgrading of wastewater treatment plants in the basin. In a similar study, Zhang et al. (2010) developed an integrated quality-quantity model to test the impact of water allocation scenarios on water quality in a river basin in China to calculate water deficit for different uses considering water quality requirements. Azevedo et al. (2000) developed a stochastic model for integration of water quality-quantity models and tested six management options formed by various reservoir operation rules and levels of wastewater treatment. All these studies were carried out using historical data. Zoltay et al. (2010) introduced an integrated watershed management model including water quality and land-use change to assess a variety of watershed management options. They considered annual net cost benefit (total revenue minus total cost) and in-stream flows as objectives, using a model that was lumped in both time (ran just for one year) and space. Although these studies aimed to integrate water quality-quantity models and addressed rivers and reservoirs water quality, none of them explicitly assessed the impacts of water quality-quantity on the reliability of public, municipal, or urban water supply.

Reliability of water supply is one of the main concerns of water utilities. Though quantification of the reliability of water supplies is a long-standing problem in water resource systems analysis (Hashimoto et al., 1982), there has been growing recent attention in the context of uncertain future climatic changes (Borgomeo et al., 2016; Borgomeo et al., 2014; Chung et al., 2009; Hall et al., 2012; Matrosov et al., 2015; Mortazavi-Naeini et al., 2014; Mortazavi-Naeini et al., 2015). There is growing recognition that the performance of water supply systems should be measured in terms of observable outcomes for water users (Hall et al., 2012), including the reliability of water supplies, or, on the other hand, the frequency, severity, and duration for which users' access to water may need to be curtailed because of water shortages. In England this performance metric is articulated in terms of levels of service (LoS), which are typically presented as return periods (e.g., 1 in 20 years) and represent the target frequencies that restrictions on water use, of a given severity (e.g., bans on watering domestic gardens), should not exceed.

Water resources management planners are increasingly aware of the effects that climate change and rising demand for water may have on the reliability of water supplies. For example, many studies have been conducted to assess potential impacts of climate change, such as changes in river flows (Arnell et al., 2014; Leavesley, 1994; Vano et al., 2010; Wilby & Harris, 2006) and water quality (Whitehead et al., 2009).

None of abovementioned studies have addressed climate change impacts on public water supply by considering both water quality and quantity impacts. This is a significant gap, as deteriorated quality in water bodies can constrain the water that is available for use for public water supplies. Therefore, we developed an integrated model of water quality-quantity for assessing impacts of climate and land-use change, up to the end of the 21st century, on the reliability of public water supplies. This methodology can help water utilities to better understand bottlenecks in their system and avoid any unseen failures. It also provides the platform for cooperation among actors in the catchment, including with farmers and industrial polluters.

To address the impact of climate change properly and assess its associated risks, it is vital to test the integrated water quality-quantity model using a large number of realizations of possible climatic conditions. Deficits in water quantity (hydrological droughts) arise from a complex interplay of natural and human factors (notably restrictions on water use as the drought develops), which, we argue, can only adequately be addressed through stochastic simulation. Harmful water quality, in rivers during periods of low flow and in water supply reservoirs, is also determined by complex dynamics that are partly driven by weather-related factors including temperature and solar radiation, which also requires a coupled simulation approach. In this study, we use a novel climate data set, called weather@home, which provides a "super ensemble" (tens of thousands of members) of weather sequences obtained from a state-of-the-art regional climate modeling experiment (Guillod et al., 2018). Weather sequences from weather@home contain synthetic drought events whose severity and frequency go beyond the historical record, allowing for extensive stress testing of the system. The weather sequences enable exploration of a range of possible climatic changes (e.g., associated with different GHG emissions and climate sensitivities) and also a large number of stochastic realizations of a given climate scenario (Borgomeo et al., 2014).

The aims of this paper are (i) to present a new water quality-quantity modeling approach, including reservoir water quality modeling, for assessing the reliability of public water supplies; (ii) to assess the impact of climate and land use change scenarios on public water supply reliability, taking into account the interplay between water quantity and water quality. We apply this methodology to the River Thames catchment, in the South of England. We couple a hydrological model of river water quality and quantity with a water resource system model that determines water withdrawals and a model of water quality in offline storage reservoirs. We demonstrated an assessment of the probability of failure to meet the required reliability or LoS in the Thames region under all combinations of the climatic and land-use scenarios.

2. Conceptual Framework

There are a variety of measures to assess a water resource system (Hashimoto et al., 1982). We used the frequency of water shortages at different levels of severity and probability of exceeding LoS as reliability metrics

(Borgomeo et al., 2014). In England, the LoS defines how rarely a water company intends to impose a given level of restrictions on water use for various categories of water users. In our coupled modeling framework, we consider water shortages that occur because (i) potentially harmful water quality means that the water utility cannot use the water for public water supply and/or (ii) because extremely low river flows mean that insufficient water may be withdrawn for public water supply. In this section, first the water quality and quantity thresholds are defined, and then the reliability metric is presented.

2.1. Water Quality Constraints on Public Water Supplies

Poor river water quality is of concern for water utilities if it raises treatment costs or increases the probability of treatment plant failure. High sediment load can block filters and silt reservoirs. High nutrient concentrations (nitrogen and phosphorus) can cause phytoplankton blooms in rivers and reservoirs, which in turn can clog filters, in the case of large phytoplankton types such as diatoms, or produce harmful toxins, in the case of cyanobacteria. In the worst cases, such as when severe cyanobacteria blooms produce toxins (Falconer, 1989; Lawton & Codd, 1991), water utilities might decide not to use that water due to the impossibility of treating it adequately to meet drinking water standards.

To quantify water quality risks for water utilities, we address two main factors that pose serious threats to water supply in the River Thames: (i) high turbidity in the river and (ii) large algal blooms in the water supply reservoirs—noting that in the Thames system, water is stored in large offline reservoirs that are filled by pumping from the river. With the aim of modeling these phenomena, we employed the INCA model (see below) to simulate (i) suspended sediment concentration in the River Thames, as a proxy measure of turbidity, and (ii) phosphorus concentration and water temperature, which determine the likelihood of the algal blooms in water supply reservoirs. Subsequently, a set of simulations were carried out with the water resources model WATHNET (see below) in which it was hypothesized that withdrawals from the river would be stopped if the water quality was poor. Finally, the PROTECH model was used to simulate phytoplankton concentrations in the reservoir water. The proposed framework is presented in Figure 3.

According to the water utility engineers, water withdrawal from the river Thames would cease if thresholds of phosphorus concentration, temperature, suspended sediment concentration, and reservoir total chlorophyll were exceeded (Thames Water, pres. comm., 2016). No objective values of these thresholds could be found, because they respond to a variety of factors, some of which depend on local conditions and on the expertise of the operators. In an attempt to formalize this *ad hoc* approach, we specify thresholds based on engineering judgement and empirical evidence provided by the water utility and the reservoir managers. However, these thresholds are context-specific and might not apply to other situations. This means that the results we present cannot be extrapolated to other catchments or other water resources systems. Nonetheless, our methodological framework is flexible, so could readily accommodate other water quality thresholds that apply in other contexts. The thresholds employed in this paper, above which water use is assumed to be interrupted, are the following:

1. Potential high river turbidity: suspended sediment concentration above 90 mg/L;
2. Potential algal bloom in river: phosphorus concentration above 0.8 mg/L and temperature above 15 °C;
3. Potential deteriorated reservoir quality: reservoir total chlorophyll above 40 mg/m^3.

The analysis explored the frequency with which there would be restrictions on public water supply given these water quality constraints combined with regulatory constraints on the quantity of river water withdrawals. This was compared with the reliability of public water supplies estimated just considering regulatory constraints on the quantity of water withdrawals during droughts. Multiple simulations were used to estimate the probability of not meeting the LoS (Borgomeo et al., 2014). Land-use and water treatment scenarios were also implemented, with the aim of understanding the potential impacts of these measures on the risk water shortages due to inadequate water quality.

2.2. Water Shortages

To mitigate shortages, water utilities either augment their supply sources or reduce their demand by emergency demand reduction strategies. Water utilities may impose different levels of restrictions on their customers' use of water if the reservoir storage level is below specific thresholds. Table 1 presents the different categories of restrictions that may be adopted for Thames Water (Thames Water, 2014a), the largest water company in the UK, operating in Southern England and serving around 15 million customers. Thames

Table 1

Levels of Service (LoS), Typical Targets (Which Vary Between Water Companies), Demand Reduction Measures Associated With This LoS, Expected Reductions in Water Use Due to Demand Reduction Measures

Level of Service (LoS) for restriction level i (LOS_i)	Target frequency (no more frequent than this target)	Demand reduction measures for domestic customers	Expected reduction in water use due to demand reduction measures (cumulative; %)
Level 1	1 year in 5 on average	Publicity about drought	2.2
Level 2	1 year in 10 on average	Partial hosepipe ban	9.1
Level 3	1 year in 20 on average	Full sprinkler hosepipe ban	13.3
Level 4	“Never”	Ban all use (standpipes in streets)	31.3

Water has a target for the frequency of imposing each of these levels of restrictions, which they aim not to exceed. This is known as the LoS. In this study, we employed the LoS as a target reliability threshold for the public water supply system and seek to quantify the conditions under which the LoS is not likely to be met.

Temporary Use Bans (Level 2) includes forbidding use of sprinklers and unattended hosepipes, while Level 3 introduces a wide range of water use limitations for business water users and spray irrigators. Emergency measures, such as cutting off household water supplies, so people have to collect water from taps in the street (sometimes known as “standpipes”) or from water tanker trucks, may be used in the most severe drought and water shortage.

The timing of imposing restrictions is dependent upon the quantity of stored water for public water supply. In Figure 1 the lower Thames Control Diagram is presented, which regulates water withdrawals from the Thames basin. This graph is based on an agreement between Thames Water and the Environment Agency (the environmental regulator). The horizontal axis shows the months in a year, and the vertical axis shows the total Lower Thames Storage in megaliters (ML), which is the total capacity of reservoirs on the Lower part of Thames for each month. The combination of the storage and river flow determines the associated level of restriction (if any) for that month.

2.3. System Reliability Measure

Following Borgomeo et al. (2014), we use the probability of exceeding LoS as a metric of system reliability. The probability defines for a given system configuration and climate/land use scenario, how likely it is those water users' expectations will not be met by the water utility. This metric does not explicitly quantify the consequences of water shortages, but the tolerability of shortages of given severity for water users (see Table 1) is implicit in the LoS.

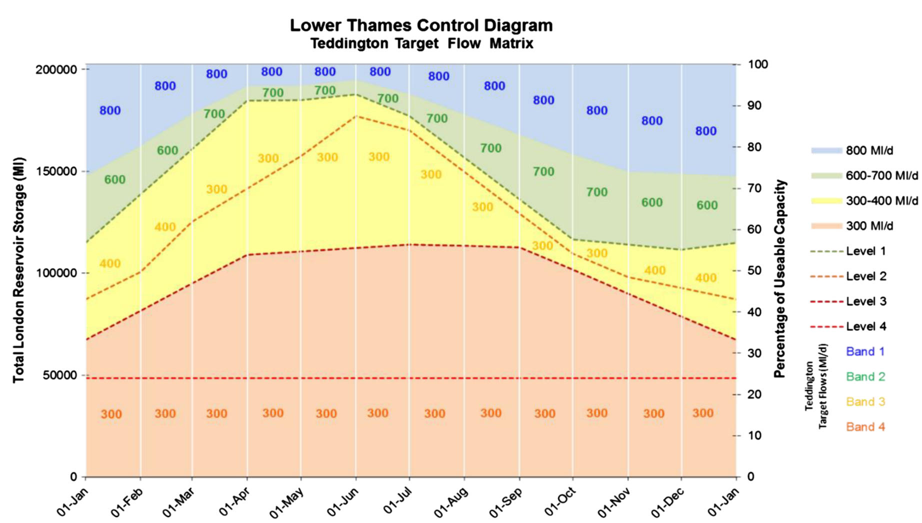

Figure 1. Lower Thames Control Diagram (LTCD), which is a function of reservoir storage and month of the year. Levels of Service and associated restrictions (see Table 1) are imposed based on the dotted lines. Required river flows are depicted by the shading (Thames Water, 2014a).

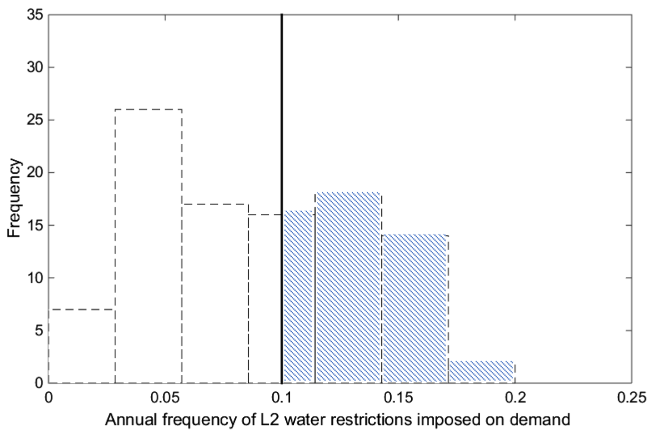

Figure 2. Typical from a large ensemble of water resource model simulations presenting a histogram of the annual frequency of restrictions of severity R_2. The solid vertical line shows the Level of Service target for restrictions of severity R_2. The ratio of the hatched area to the nonhatched area is an estimate of the probability of exceeding LoS_2

A Monte Carlo simulation method is employed for the reliability assessment. The water resource system model is run with the time series of inflows subject to future demand growth, climate scenarios, and land-use changes. Then, for each simulation k and for each year t, we record the number of times a water restriction of severity R_i occurs, where i denotes the level of restrictions. The water resource system is run for S_k: $k = 1, \ldots, m$ number of simulations to estimate the frequency $f(R_i, t)$ of a demand restrictions of severity R_i in each year t. This frequency is estimated by dividing the number of simulations in which R_i happened in year t by total number of simulations.

Running the water resources system model for a set of n realizations of each climate and land-use scenarios produces a histogram of the frequency $f(R_i, t)$ of restrictions of severity R_i. Figure 2 presents an example of a typical distribution for the frequency of restrictions. The black vertical line in Figure 2 represents LoS for the given level of restrictions; for instance, it is 0.1 for LoS_2. The probability of exceeding the LoS is estimated as the proportion of simulated instances that exceeds LoS_i (the dashed area in Figure 2).

In this study, in addition to the measures that determine system reliability with respect to water quantity (described above, following Borgomeo et al., 2014), we also impose quality-related constraints on water withdrawals and treatment of reservoir water, as described in section 2.1.

3. Models

In this section the water quantity and quality models employed in this study are presented. The water resources model simulates the river flows, reservoir operation, and demands. Two water quality models are applied, respectively, for river and reservoir water quality.

3.1. Water Resource System

Simulation models are used widely to simulate the behavior of the water resource systems for a given set of input conditions. These models can be generally categorized into two groups, namely reservoir-system-simulation models and system-analysis models (Labadie, 2004; Wurbs, 1993). System-analysis models are based on network-flow programming, which has been applied in a variety of operations research and systems engineering applications. These models represent the main entities within the water resource system as a set of nodes and arcs, with the nodes representing source, storage, demand, or transfer points and the arcs representing streams or pipes.

There exist a number of generalized models based on network-flow programming, and in this study, the WATHNET simulation model (Kuczera, 1992) is employed. WATHNET was selected for the following reasons: (1) the efficient computation time and capability of running on parallel nodes; (2) the availability of the source code allowed for its adaptation to the new requirements of this study; (3) the scripting feature that facilitates introducing any rules or constraints; and (4) its architecture facilitates the implementation of multi-objective optimization and handling optionality. WATHNET has been successfully used in many studies of water supply systems (Borgomeo et al., 2016; Mortazavi-Naeini et al., 2014; Mortazavi-Naeini et al., 2015; Mortazavi et al., 2012).

3.2. Surface Water Quality Model

The INCA hydrological and water quality model was used to simulate the water, sediment, and phosphorus cycle of the River Thames. The INCA model was originally a nitrogen (Whitehead et al., 1998) and phosphorus (Wade, Whitehead, & Butterfield, 2002) model. Several submodels have subsequently been added, including soil erosion and sediment transport (Lázár et al., 2010). In this study, the phosphorus version of INCA (INCA-P) was employed, which also includes the sediment submodel. The INCA suite of models has already been applied to various basins across the UK and Europe (Wade et al., 2004). The INCA model is semidistributed and process-based, reproducing the rainfall-runoff transformation and river routing using simple mass-balance first-order differential equations (Wade, Durand, et al., 2002). It is driven by a series of precipitation, temperature, hydrologically effective rainfall, and soil moisture deficit. The hydrologically effective rainfall and soil moisture deficit are estimated using another semidistributed hydrological model, called PERSiST (Futter et al., 2014). PERSiST uses a temperature-based method to compute the evapotranspiration, and it computes the soil moisture through a balance between net rainfall, evapotranspiration, infiltration, percolation, and subsuperficial flow. The sediment submodel of INCA has been presented in several sediment-focused papers (Jarritt & Lawrence, 2007; Lázár et al., 2010; Rankinen et al., 2010). It is also a component of the phosphorus, carbon, pathogen, and organic contaminant versions of the INCA model, due to absorption processes and interaction with bed sediments (Crossman et al., 2013; Futter et al., 2007; Lu et al., 2016; Nizzetto et al., 2016; Wade, Whitehead, & Butterfield, 2002; Whitehead et al., 2016). A sensitivity/uncertainty analysis of its structure and parameters can be found in Jackson-Blake and Starrfelt (2015).

The phosphorus submodel of INCA (Wade, Whitehead, & Butterfield, 2002) reproduces hillslope and river channel phosphorus dynamics. This submodel also uses a semidistributed representation, thus accounting for the impacts of different management practices, such as fertilizer application and wastewater discharge. The model equations are divided into two main parts: land phase and in-stream. The land phase submodel is a simplified representation of the soil processes that involve phosphorus, including mineralization, microbial decomposition, immobilization, plant uptake, and conversion of readily available phosphorus to firmly bound and vice versa. The in-stream submodel routes water and phosphorus downstream. Sorption/desorption and interactions with bed sediment are also taken into account. INCA-P simulates organic and inorganic phosphorus concentrations in soils and total phosphorus (dissolved plus particulate phosphorus) concentration in the river channel flow. Stream water temperature is modeled as a linear function of the air temperature.

3.3. Reservoir Water Quality Model

The PROTECH model was used to estimate the growth of phytoplankton in the catchment's reservoirs. PROTECH (Phytoplankton RespOnses To Environmental CHange) is a process-based phytoplankton reservoir/lake community model that has been used for nearly 20 years (see Elliott et al., 2010; Reynolds et al., 2001). It simulates the daily growth of several phytoplankton species throughout a 1-D vertical water column in response to changing environmental conditions such as light, temperature, and nutrient availability.

For each species, its growth is expressed as the daily change in the chlorophyll *a* concentration ($\Delta X/\Delta t$):

$$\Delta X/\Delta t = (r' - S - G - D)X \tag{1}$$

where r' is the growth rate defined as the increase over 24 hr, S is the loss due to settling out from the water column, G is the loss due to zooplankton grazing, and D is the loss due to dilution caused by hydraulic exchange. The growth rate (r') is further defined by the following:

$$r' = \min\left(r'_{(\theta,I)}, r'_{\mathrm{P}}, r'_{\mathrm{N}}, r'_{\mathrm{Si}}\right) \tag{2}$$

where $r'_{(\theta,I)}$ is the growth rate at a given water temperature and light level and r'_{P}, r'_{N}, and r'_{Si} are the growth rate limitations determined by phosphorus, nitrogen, and silicon concentrations that fall below these respective threshold concentrations: <3, 80, and 500 mg/m^3 (Reynolds, 2006). The r' values are phytoplankton-dependent, relating to their morphology and nutrient demands.

In this study, a response equation was estimated based on multiple simulations of the PROTECH model to predict the chlorophyll concentration given certain key drivers. To this end, PROTECH was driven using 100 weather@home climatic scenarios over three time periods (baseline: 1975–2004, near future: 2020–2049, and far future: 2070–2099) and coupled with the corresponding nutrient values from the INCA models at the reservoir withdrawal point in the Thames river. In addition, the predicted reservoir water balance from WATHNET was used, which provided a large range of reservoir water levels. In total, this gave 3,287,400 days of predicted chlorophyll values.

Initially, the following independent variables were examined: river P concentration, river temperature, and reservoir depth. This examination showed that river P concentration and the predicted chlorophyll were not normally distributed, and thus, they were log transformed.

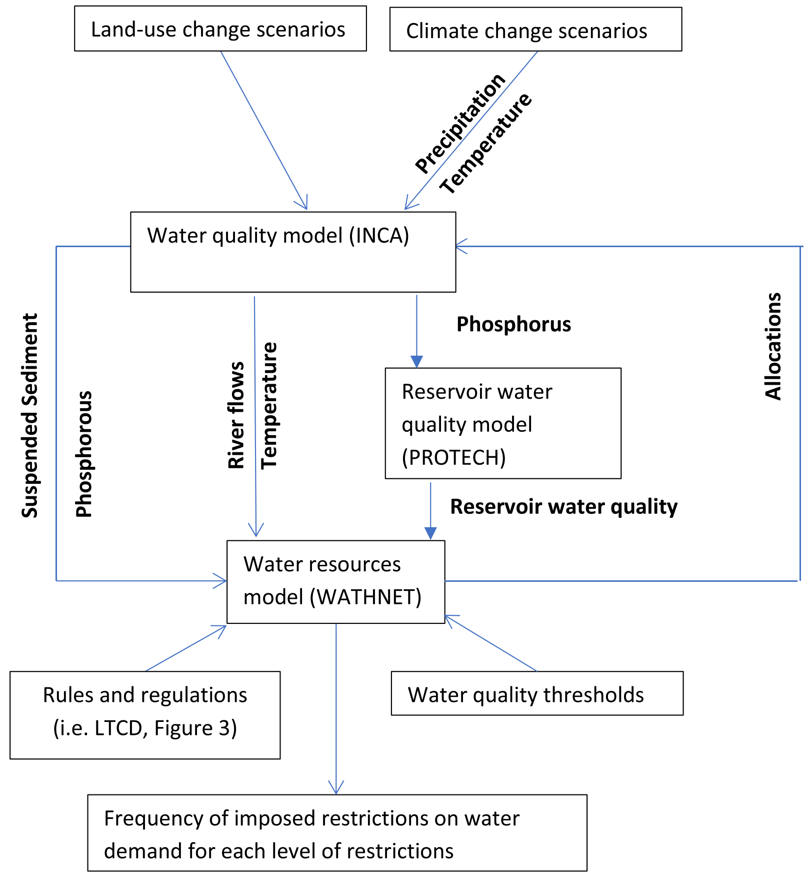

Figure 3. Flowchart of data and model sequence, showing interactions between water qulaity (INCA) and water quantity (WATHNET) model, to calculate model outputs in terms of frequency of imposed restrictions on water use for each level of service.

Several different quadratic equations were tested using these drivers, and their residual sum of squares in combination with their Akaike information criterion were analyzed using R (R Core Team, 2017). The former assesses the goodness of fit of the equation while the latter judges the quality of the model. The analysis suggested that the equation below was the best for balancing its goodness of fit ($R^2 = 0.56$, $p < 0.001$) with model complexity:

$$\ln Chl = -0.5643 + 0.5845 \times \ln P_{\mathrm{River}} - 0.04748 \times z + 0.09266 \times T_{\mathrm{River}} \tag{3}$$

where Chl is the reservoir total chlorophyll (mg/m^3), P_{River} is the river P concentration (mg/m^3), z is the reservoir depth (m), and T_{River} is the river temperature (°C).

4. Modeling Strategy

The flowchart in Figure 3 presents the interaction between the water resource model (WATHNET), the water quality model (INCA), and the reservoir model (PROTECH). First, we run the INCA model to produce river flows driven by precipitation and temperature data. The river flows are then passed to WATHNET to simulate water withdrawals and allocations. INCA is then rerun to calculate the water quality at each abstraction point, this time also using abstraction data provided by WATHNET. This is done because water abstraction (i.e., reduction in the quantity of water in the river) can alter significantly the water quality just downstream of the abstraction point. Finally, the water quality results from INCA are passed to WATHNET and PROTECH and used as constraints on water abstractions; that is, when the water quality does not meet certain criteria (water quality restrictions), abstractions are stopped. WATHNET calculates the frequency of imposed restrictions on water use for each level of restrictions, for two scenarios: (i) just considering water

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quantity (as in previous assessments) and (ii) also considering the water quality (consists of river and reservoir water quality) criteria presented in section 2.1.

The same workflow is repeated for three proposed climatic scenarios (section 5.1) and three land use scenarios (section 5.2).

5. Scenarios

The system of models outlined in the previous section was used to explore the risk of water shortages and harmful water quality impacting the reliability of public water supplies under a range of climate and land use scenarios. In this section we present these scenarios.

5.1. Climate Scenarios

A number of previous studies have examined the impacts of climate change on water resources in the Thames Basin (Borgomeo et al., 2014; Fung et al., 2013; Manning et al., 2009; Wilby & Harris, 2006). Most recent studies have used probabilistic outputs from the UKCP09 scenarios (Murphy et al., 2009). Here we employ a more recent large ensemble of climate model projections based on the same climate models as UKCP09 (HadCM3 and HadRM3) but with a much larger number of realizations, using the weather@home system (Guillod et al., 2018; Massey et al., 2015). Weather@home uses an atmospheric global climate model and a regional climate model sharing essentially the same physics, which are run on volunteers' computers around the world using the infrastructure of climateprediction.ne (Guillod et al., 2018). The freely-running atmospheric global climate model (HadAM3P), driven by sea surface temperature and sea ice boundary conditions that reflect long-term warming effects, is downscaled at 25 km over Europe by the regional climate model (HadRM3P). Version 2 of weather@home (Guillod et al., 2018), used in these simulations, includes an improved land surface scheme to better represent the long memory effects of soil moisture during droughts.

Long continuous times series were generated for the UK over three periods, namely the recent past (1900–2006, out of which 1975–2004 form a baseline, hereafter BS), the near future (2020–2049, NF) and the far future (2070–2099, FF). The algorithm for concatenating year-long simulations (Guillod et al., 2018) avoids discontinuities in soil moisture, which is the main source of memory in the simulations given sea ocean state (sea surface temperatures, sea ice). For the future time periods (NF and FF), five scenarios are provided that sample climate model uncertainty with respect to future changes in the ocean state (Guillod et al., 2018). In this study, the central scenario is used, which is based on the median ocean warming pattern for RCP8.5 derived from CMIP5 coupled Atmosphere-Ocean General Circulation Model outputs (Taylor et al., 2012). A total of 100 time series were available for each time period (BS, NF, and dFF) and represent 100 different trajectories of weather patterns that are consistent with the anthropogenic and natural drivers. The time series have been validated and performed well for all variables, with the exception of summer precipitation that has been bias-corrected using monthly linear bias correction factors. In particular, long dry sequences have been shown to be well represented in the time series (Guillod et al., 2018). Figure 4 shows the monthly precipitation and temperature projections for the River Thames catchment for the BS, NF, and FF climate scenarios.

5.2. Land-Use Scenarios

To assess the impacts of land use and land management on the water quality, three scenarios were defined: (i) LU-baseline: current land use; (ii) LU-future: future land use, that is, expansion of agricultural land due to increased food demand; and (iii) LU-future + mitigation: future land use with enhanced phosphorus mitigation strategies. These scenarios are consistent with the ones used in Bussi, Whitehead, et al. (2016). The future land use scenario (ii) describes an increase in agricultural land area. The scenario represents a situation in which food security is a dominant driving force for land use change. The land allocation and crop arrangement were quantified using the land cover model LandSFACTS (Castellazzi et al., 2010) with a corresponding reduction in grassland and forest land fractions. For the case study reported here, this land-use scenario shifts land use from an almost equal proportion of arable land and grassland to double arable land at the expenses of forest land and grassland. The future land use scenario and mitigations strategy (iii) define a situation where the agricultural land expands but with reduction of fertilizer use and phosphorus removal from wastewater. Crossman et al. (2013) and Whitehead et al. (2013) demonstrated that this strategy is the most effective one for the control of phosphorus concentrations in the River Thames. The phosphorus

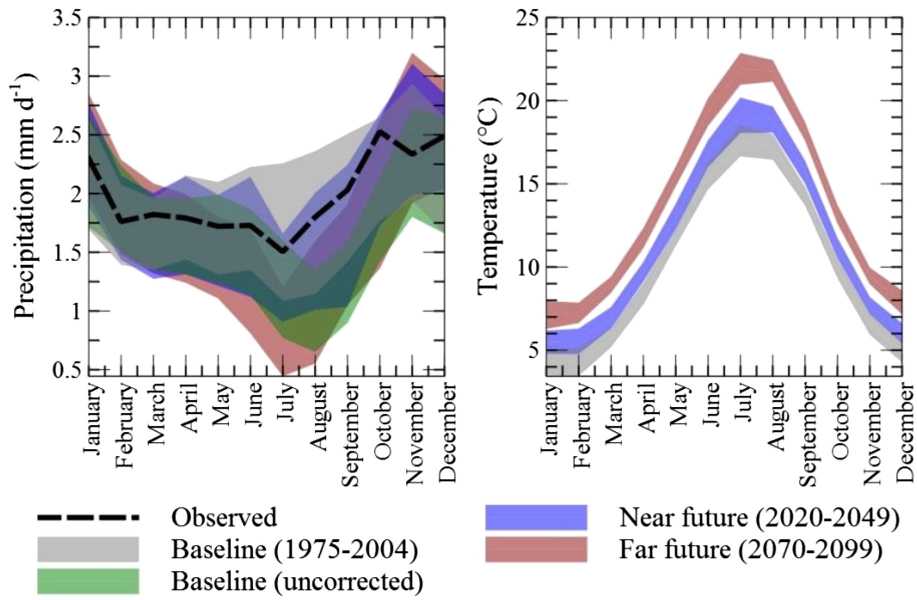

Figure 4. Monthly average values of precipitation, raw and bias-corrected, and temperature projections for the River Thames catchment, for baseline, near future (NF), and far future (FF) climate scenarios. Where indicated, the series represent the weather@home outcome before bias correction.

mitigation strategy incorporated a 20% reduction in the fertilizer application rates and applying a limit of 0.3 mg/L of total phosphorus in wastewater discharge from sewage treatment works. More details about the model parameterization for land use and management impact analysis in the River Thames can be found in Crossman et al. (2013), Bussi, Dadson, et al. (2016), and Bussi, Whitehead, et al. (2016).

6. Case Study

6.1. Background

Water resources management plans in England and Wales are developed at water resource zone level (WRZ). A WRZ is defined as an area where water users experience the same level of water shortages (Environment Agency, 2012). All Thames Water WRZs are used in this study as shown by green colored areas in Figure 5. The Thames Water supply area comprises six WRZs: London, SWOX (Swindon and Oxford), Henley, Kennet Valley, SWA (Slough, Wycombe, and Aylesbury) and Guildford.

The London WRZ is the most populated area in the country, with around 7 million water users. The primary source of water for the London WRZ is surface water abstractions from River Thames and River Lee, directly or via pump to storages. The river abstractions provide about 80% of demand, and the remainder is supplied by groundwater abstractions. The other five WRZs supply water to 2.1 million people, and their source is mainly from groundwater, which is supported by surface water abstractions and storages in the upper River Thames (Thames Water, 2014a).

The population in the region has increased in the last decade, and it is expected to increase in the future. A fixed rate of 0.5% annual demand growth was assumed for London for the future scenarios analyzed in this study (Borgomeo et al., 2016).

6.2. Hydrology and Water Quality Validation

The INCA model has been calibrated and validated for the River Thames in several previous studies (Bussi, Dadson, et al., 2016; Bussi et al., 2017; Whitehead et al., 2013), with satisfactory model performances in terms of reproduction of flow and nutrient concentration. In this study, for the hydrological submodel calibration and validation, records of continuous daily water discharge at several sections of the River Thames were obtained from the National River Flow Archive (ceh.ac.uk/data/nrfa/). The sediment and phosphorus sub-models were calibrated using weekly observations of suspended sediment concentration and phosphorus

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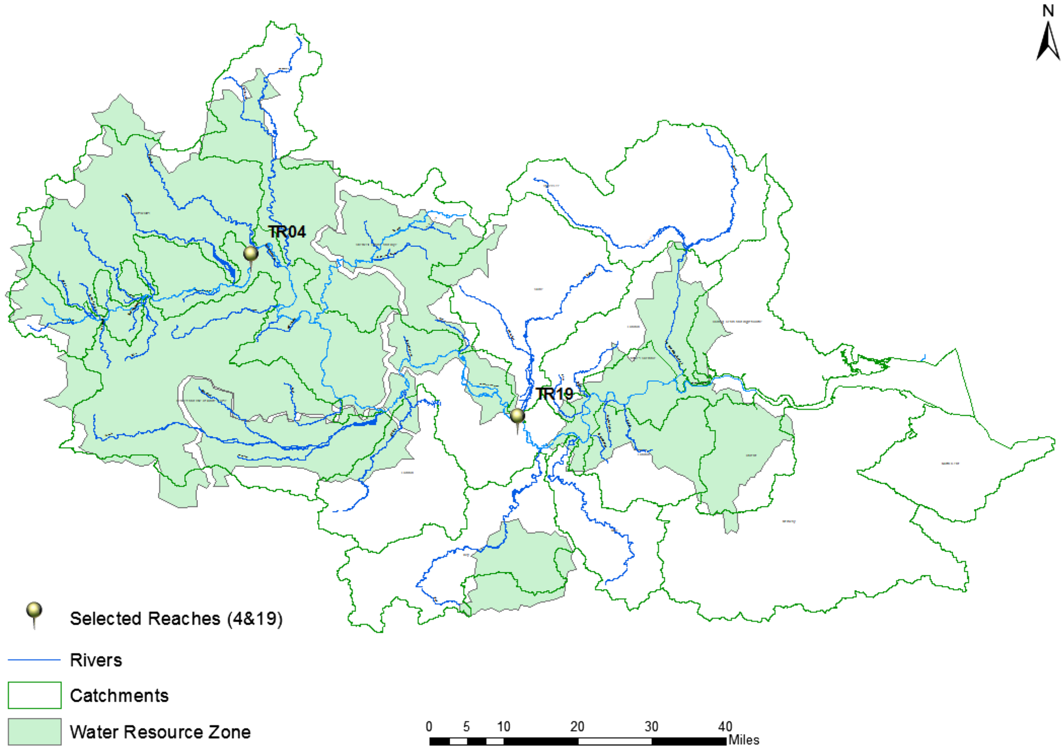

Figure 5. The catchments and rivers of Thames region. The shaded areas are Thames Water water resource zones (WRZs). Two selected reaches, numbers 4 and 19, are shown.

concentration from the Thames Initiative research platform data set (Bowes et al., 2012), collected by the UK Centre of Ecology and Hydrology (CEH).

Sensitivity analysis (Spear & Hornberger, 1980; Whitehead et al., 2015) was used to identify the following parameters as being the most influential on model performance: Flow parameters (direct runoff residence time, soil water residence time, ground water residence time, threshold soil zone flow, rainfall excess proportion, maximum infiltration rate, and discharge/velocity relationship coefficient and exponent), nitrate and ammonium parameters (denitrification rate in soil and river, nitrification rate in soil and river, mineralization rate in soil, immobilization rate in soil, fertilizer addition rate in soil, and plant uptake), phosphorus parameters (fertilizer addition rate in soil, plant uptake, and liquid manure/fertilizer usage), and sediment

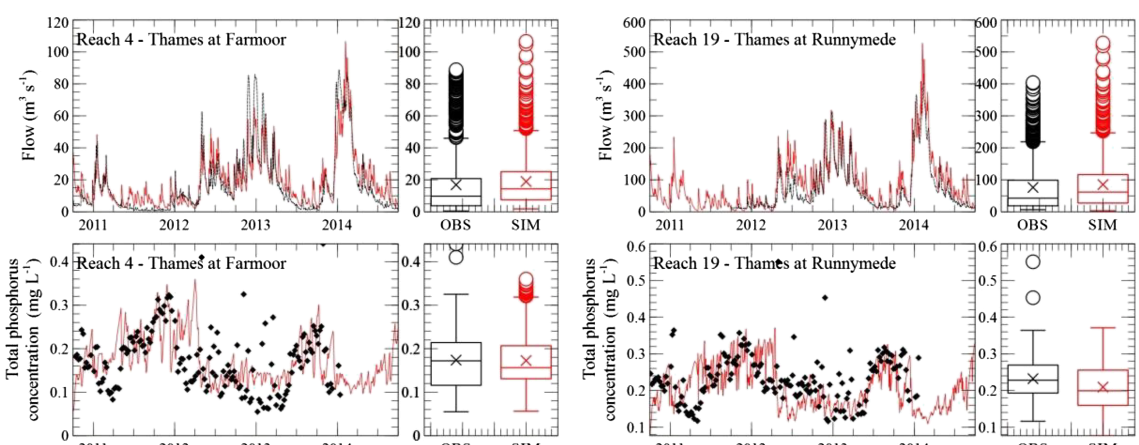

Figure 6. INCA model calibration results for flow and phosphorus in river reaches 4 and 19. OBS is observed (black) and SIM is simulated (red). Please refer to Bussi, Dadson, et al. (2016) for the sediment concentration calibration results.

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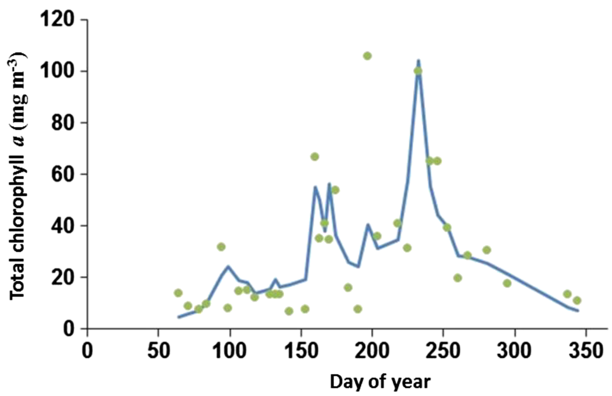

Figure 7. Comparison between observed (green dots) and modeled total chlorophyll *a* (blue line) for Farmoor reservoir 2014.

parameters (splash and flow erosion parameters, transport capacity parameters, entrainment, and bank erosion parameters; see Bussi, Whitehead, et al., 2016, and Jackson-Blake & Starrfelt, 2015, for more details). A total of 10,000 different sets of these parameters were generated. The parameter set that performed best with respect to observed flow, suspended sediment concentration, and total phosphorus concentration at two stations (reach 4 and reach 19), using data from October 2010 to September 2014 (Figure 6) was identified based on the Nash and Sutcliffe Efficiency (NSE; Nash & Sutcliffe, 1970) and the percent bias (PBIAS; Moriasi et al., 2007).

6.3. Reservoir Water Quality Model Calibration

The PROTECH model was initially calibrated using data from a reservoir 8 km west of the city of Oxford. Farmoor reservoir supplies water to the major urban areas of Swindon and Oxford in addition to areas of north Oxfordshire and has a maximum depth of 13 m and a total storage volume of 1,4270 ML. To drive the simulation, meteorological data for 2014 was taken from Brize Norton metrological station 15 km to the west. For 2014, reservoir phytoplankton abundance data were available in the form of total chlorophyll *a* concentrations, and there were some qualitative data for the relative abundance of phytoplankton species. The latter were used to select the eight most representative types from PROTECH's phytoplankton library. After some minor adjustments to increase the observed relative humidity values used to drive the simulation, the model captured reasonably well the seasonal changes in phytoplankton biomass ($R^2 = 0.63$; Figure 7).

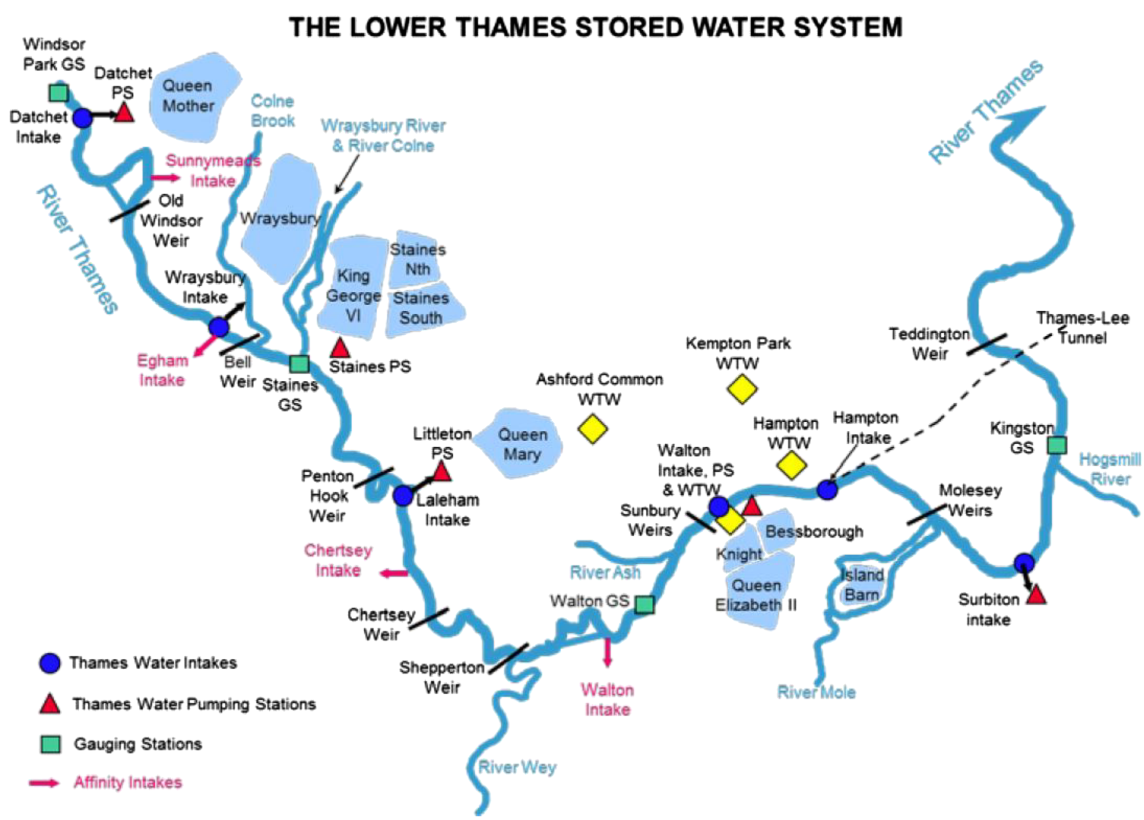

Figure 8. Schematic of the Lower Thames water resources system, showing Thames Water's storage reservoirs and the intakes for the neighboring water company that also uses water from the River Thames:Affinity Water (Thames Water, 2014b).

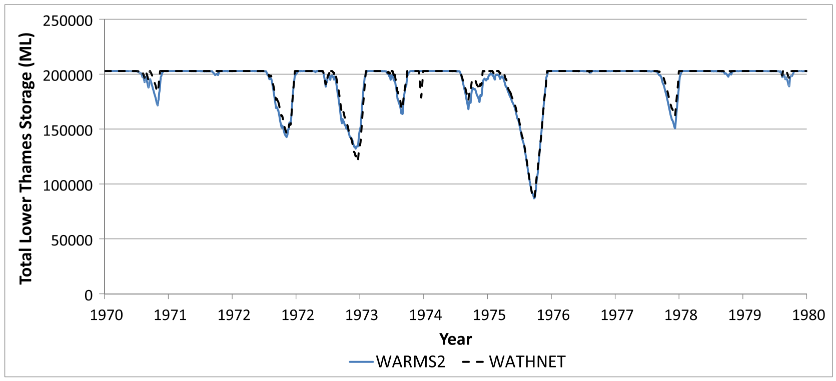

Figure 9. Storage levels in the Lower Thames reservoirs. Comparison of WATHNET simulations and Thames Water's operational model for 1970–1980.

6.4. Water Resources System Validation

The Thames water resources system model was built in WATHNET which enabled running many simulations in reasonable time and integration of the model with INCA model. The water resources model developed in this study is a complex model with more than 100 nodes and 200 arcs. It includes all WRZs in the Thames region from the upper Thames to lower Thames (i.e., London). The computation time of the model for 30 years of daily time step simulation on a 3.40-GHz desktop PC is around 140 s. Figure 8 shows a schematic of the water resource system in the Lower Thames.

As observed reservoir levels were not available, validation of WATHNET was achieved by comparison with storage levels obtained by Thames Water's operational model (WARMS2) using the same input data (daily inflows from 1920 to 2010). Figure 9 presents the storage level of both models for the 1970–1980 periods. The figure indicates that WATHNET effectively reproduces the storages levels in WARMS2 model (Nash and Sutcliffe Efficiency (NSE) = 0.98 and percent bias (PBIAS) = 0.2). To better understand the compatibility of two models, in Figure 10 the cumulative probability of Lower Thames storages are compared. As the figure shows, two models performed similarly, with WATHNET slightly underestimating storage volumes below 15,000 ML and slightly overestimating storage levels above 15,000 ML.

7. Results

7.1. Water Quality Scenarios

The monthly average results of the INCA model can be seen in Figure 11. Here the monthly averages of flow, suspended sediment, and total phosphorus concentration resulting from the INCA model driven by the

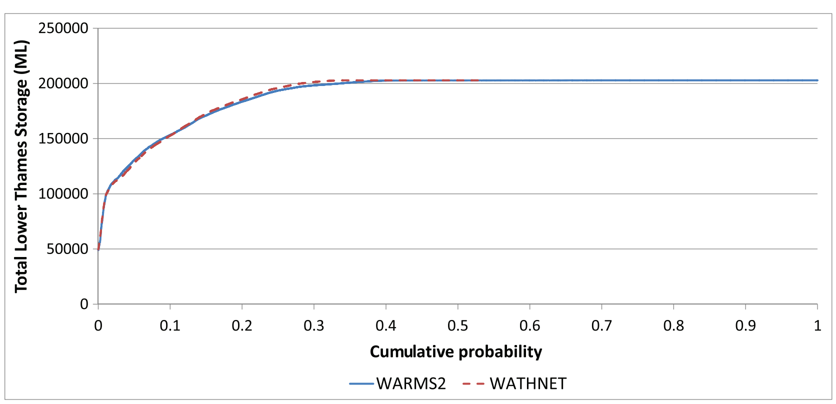

Figure 10. Storage levels in the Lower Thames reservoirs. Comparison of WATHNET and Thames Water's operational model (WARMS2) for cumulative probability of Lower Thames storage.

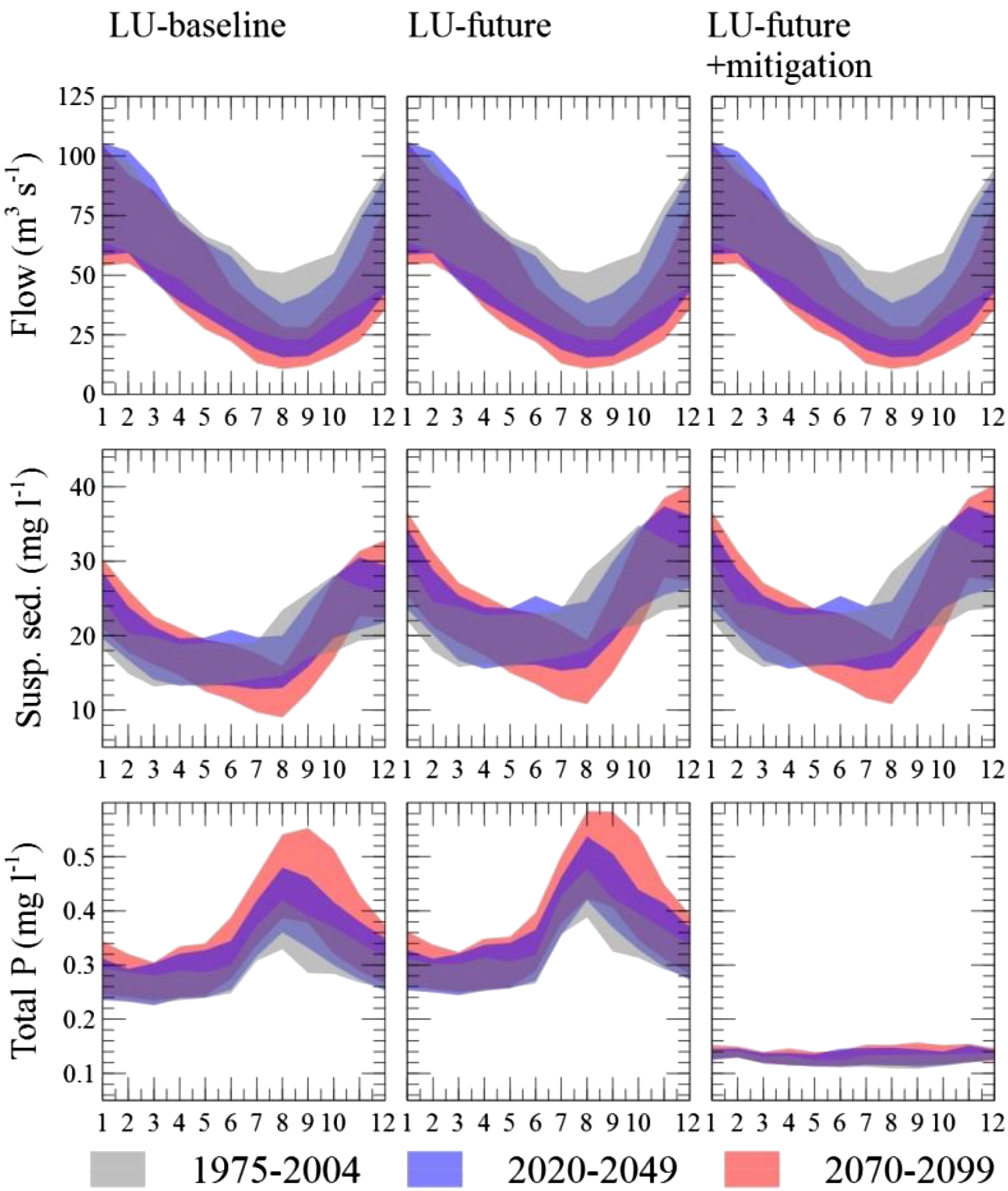

Figure 11. Monthly averages of flow, suspended sediment concentration, and total phosphorus concentration for the Lower Thames (reach 19), computed with the INCA model under the weather@home climatic scenarios over three time slices (baseline: 1975–2004, near future: 2020–2049, and far future: 2070–2099) and under three different scenarios of land use: baseline, future, and future with water quality mitigation actions.

weather@home climate data are shown for the Lower Thames, for the three time horizons (baseline: 1975–2004; near future: 2020–2049; far future: 2070–2099) and for all three land use scenarios (current land use, expansion of agriculture, combined reduction of fertilizer use, and phosphorus stripping from wastewater). It can be observed that climate change is expected to reduce summer flows and consequently also the suspended sediment concentration, although an increase in suspended sediment concentration is predicted to occur in some scenarios of the far future due to an increase in extreme winter floods. Total phosphorus

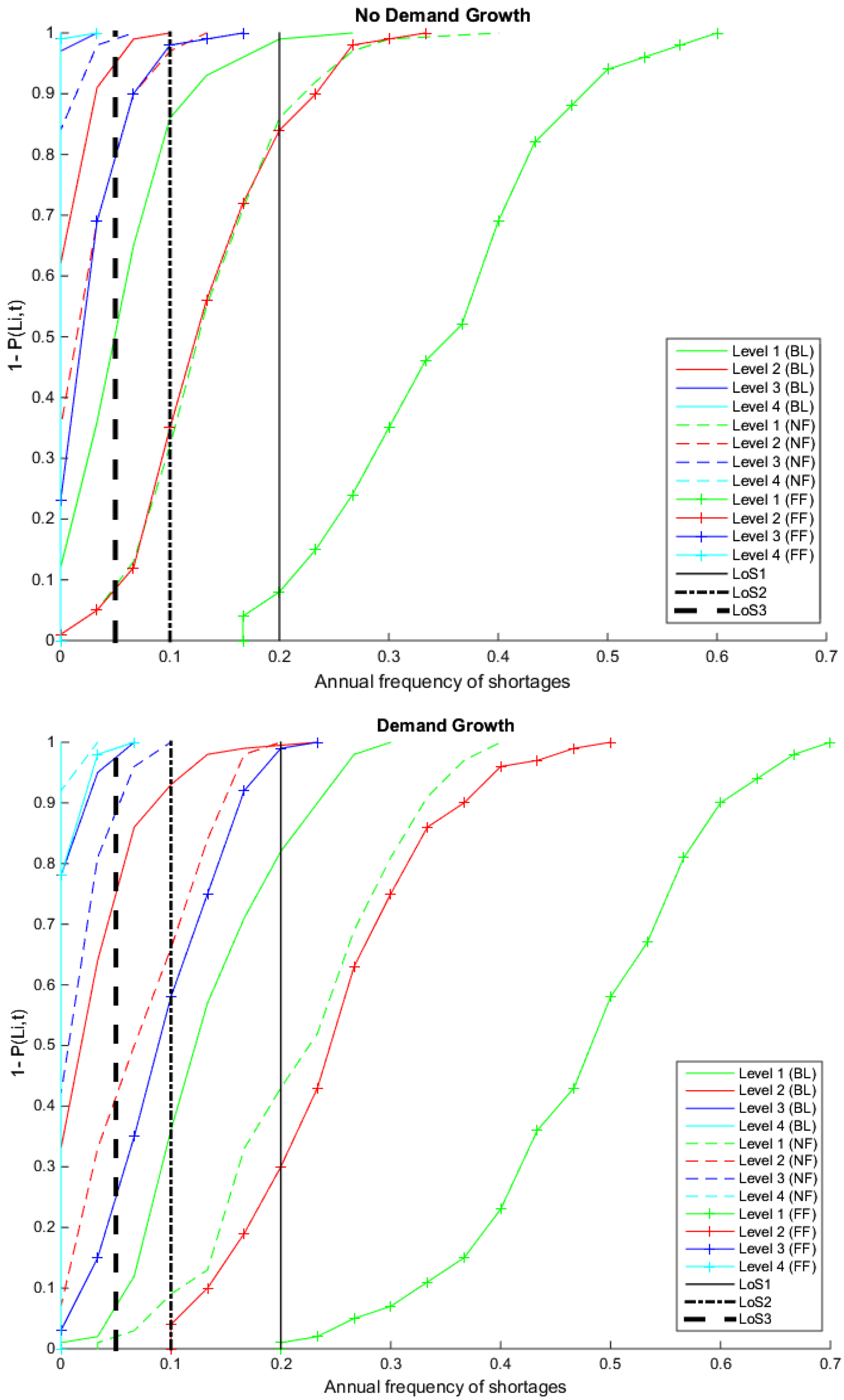

Figure 12. Impact of climate change scenarios on probability of exceeding LoS, just considering water quantity. The vertical lines represent the Thames Water's LoS for each level of restrictions. LoS = Level of Service, BL = baseline, NF = near future, FF = far future.

Table 2
Probability of Exceeding LoS for Four Levels of Restrictions With and Without Water Quality Limitations for the Baseline, Near Future, and Far Future Time Horizons

Climate scenarios	WQQ scenarios	Probability of LoS exceedance			
		LoS_1	LoS_2	LoS_3	LoS_4
BL	WQ-with RQ	0.84	0.66	0.46	0.3
	WQ-without RQ	0.24	0.1	0.065	0.03
	NO WQ	0.18	0.07	0.025	0
NF	WQ-with RQ	1	0.96	0.92	0.45
	WQ-without RQ	0.78	0.5	0.345	0.19
	NO WQ	0.57	0.34	0.115	0.08
FF	WQ-with RQ	1	1	1	0.96
	WQ-without RQ	1	1	0.985	0.72
	NO WQ	0.99	0.96	0.75	0.22

Note. WQQ = water quality-quantity, WQ = water quality, RQ = reservoir water quality limits, LoS = level of service, BL = baseline, NF = near future, FF = far future.

Table 3
Impacts of Land-Use Change Scenarios on the Probability of Exceeding the Four Levels of Service and for Three Climate Change Scenarios for the Three Time Horizons—With and Without Reservoir Water Quality

WQQ scenarios	Climate scenarios	Land use scenarios	Probability of LoS exceedance			
			LoS_1	LoS_2	LoS_3	LoS_4
WQ-without RQ	**BL**	LU-baseline	0.24	0.1	0.065	0.03
		LU-future	0.25	0.15	0.095	0.06
		LU-future + mitigation	0.17	0.07	0.035	0.03
	NF	LU-baseline	0.78	0.5	0.345	0.19
		LU-future	0.81	0.65	0.5	0.29
		LU-future + mitigation	0.71	0.36	0.13	0.1
	FF	LU-baseline	1	1	0.985	0.72
		LU-future	1	1	1	0.83
		LU-future + mitigation	1	0.97	0.785	0.23
WQ-with RQ	**BL**	LU-baseline	0.84	0.66	0.46	0.3
		LU-future	0.83	0.66	0.445	0.3
		LU-future + mitigation	0.79	0.64	0.435	0.3
	NF	LU-baseline	1	0.96	0.92	0.45
		LU-future	1	0.96	0.92	0.49
		LU-future + mitigation	0.99	0.95	0.9	0.47
	FF	LU-baseline	1	1	1	0.96
		LU-future	1	1	1	0.96
		LU-future + mitigation	1	1	1	0.94

Note. WQQ = water quality-quantity, WQ = water quality, RQ = reservoir water quality limits, LoS = level of service, BL = baseline, NF = near future, FF = far future.

is expected to increase, especially during low flows, due to the reduced dilution capacity of the river. Land-use change is not expected to have a substantial impact on flows, as observed by Crooks and Davies (2001). However, an increase in agricultural land is expected to increase soil erosion and thus suspended sediment concentration (Bussi, Dadson, et al., 2016), as well as the total phosphorus concentration. For the mitigation scenario, the combined reduction of phosphorus from diffuse and point sources is expected to decrease dramatically the concentration of phosphorus in the River Thames, as pointed out by Bussi, Whitehead, et al. (2016), Crossman et al. (2013), and Whitehead et al. (2013), especially because of the strong reduction of the phosphorus inputs from sewage treatment works, which are the main source of phosphorus pollution in the lower Thames (Bowes et al., 2014). A residual P concentration of around 0.1 mg/L is expected to be found in the river, mainly due to atmospheric deposition and fertilizers. However, it must be noted that this is an ideal scenario where P stripping is implemented extensively, efficiently, and on all sewage treatment works. While the likelihood of this scenario is unknown a priori, these findings illustrate that a strategy consisting in extensive P reduction in wastewater can be effective in mitigating the negative impacts of climate change on river water quality.

7.2. Water Quantity

Figure 12 presents the impact of climate change on water availability for use by Thames Water for public water supply. The graph shows the probability of imposing the four levels of restrictions for three climate change scenarios with and without demand growth. The vertical lines represent the Thames Water's LoS for each level of restrictions. For instance, the first right-hand side vertical line is presenting LoS for level 1 of restrictions (LoS_1), which is 1 in 5 years or 0.2. There is no vertical line representing LoS_4, which represents Thames Water's current target to never impose level 4 restrictions.

Figure 12 shows that the probability of exceeding LoS increases in time. In the case of constant demand (no demand growth), for LoS_1 the probability of not meeting LoS for BL is 2% and for NF is 20% while the probability of exceeding LoS in FF scenario is more than 90%. LoS_2 and LoS_3 are satisfied for BL scenarios but not for NF and FF scenarios. The probability of exceeding LoS_4 in FF scenario is about 2%, which means LoS_4 was not met for this scenario.

Increasing water demand puts more pressure on the system, so the probability of failing to meet target LoS increases. In Figure 12 the probability of exceeding LoS for each level of restrictions are presented in the presence of demand growth. In this case none of the scenarios could meet LoS except LoS_4 for the BL scenario.

7.3. Water Quality

We first compared the results with and without water quality limitations on water withdrawals. We ran the WATHNET model with and without reservoir water quality limits, which we called “WQ-with RQ” and “WQ-without RQ,” respectively. In Table 2 the probability of exceeding LoS for each of the climate and water quality scenarios are presented. In all the scenarios, having water quality limitations in place increased the likelihood of exceeding the LoS. This means if the water quality is not considered, then the probability of LoS exceedance is underestimated. As we

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move toward future scenarios, the possible constraints on abstractions due to adverse water quality increases, relative to the case in which just water quantity is considered. The effect on the probability of LoS exceedance of including reservoir water quality (WQ-with RQ) is greater than the effect of just considering river water quality. For the water quality criteria used here, the effect of incorporating water quality (both in-river and in-reservoir) in the analysis is of the same order as the projected effect of climate change. This again highlights the possibility of underestimated probability of LoS exceedance without having integrated water quality model, which not only models river quality but also reservoir quality.

Table 3 demonstrates the impacts of land-use change scenarios on the probability of imposing restrictions for three climate change scenarios. When reservoir water quality is excluded (WQ-without RQ), the results show that the LU-future + mitigation scenario performed better than LU-baseline, while the LU-future is worse than the LU-baseline. These results indicate that phosphorous removal from the discharges of upstream wastewater treatment works together with agricultural practices that use less fertilizer can have a large impact on water quality, which may potentially impact on the reliability of supplies to water users in the Thames region. The potential impact of water quality constraints in water withdrawals becomes greater for NF and FF scenarios as there are larger gaps between LU-future + mitigation and LU-future or LU-baseline in these climate change scenarios, especially for L3 and L4 of restrictions. However, the land use mitigation scenario is not sufficient to recover from the projected effects of climate change, even in the near future (NF).

When the reservoir water quality is included, the results in Table 3 show that the probability of LoS exceedance increases for NF and FF climate scenarios compared to the BL scenario. However, in this case there is less to differentiate among the three land-use scenarios compared to the results of WQ-without RQ especially for NF and FF climate scenarios. This indicates that consideration of reservoir water quality reduces sensitivity to land-use changes, as the reservoir water quality dominates the system reliability, yet it is not sensitive to suspended concentrations in the river, which is one of the main impacts of land use change.

8. Conclusion

Traditionally, water resources managers have made decisions primarily based on the availability of water, though they have recognized the risk that harmful water quality poses to public water supplies. In this paper, we have proposed an integrated water quality-quantity framework to assess the reliability of water supplies. The framework incorporated stochastic simulation of river and reservoir water quality models, coupled with a water resource system model. A novel large ensemble of climate model simulations was used to investigate climatic influences upon water quantity and quality, in the catchment and in storage reservoirs. The impact of weather conditions on water demand has not been incorporated in this study.

We tested the proposed method on Thames region using water demand, climate, and land-use change scenarios. The results indicate a reduction in the reliability of water supplies, that is, an increase in the probability of failing to meet the target LoS, by up to 54% for near future scenarios and up to 83% for far future scenarios. This result applies to the current water supply system configurations and does not account for planned interventions in supply and demand, which are expected to be implemented in order to secure water supplies in the future. The presented probabilities have been estimated based on 100 realizations for each climate scenario. For more accurate probability estimates, the number of scenarios should be increased. Our results are also contingent upon the water quality criteria that determine the usability of river and reservoir water for public water supplies. Unlike the quantity of water abstractions, which are regulated according to transparent rules, water quality criteria tend to be based upon local practices and considerations at individual water treatment works that are not clearly articulated.

Having water quality limitations on river water abstractions is predicted to reduce reliability of public water supplies. Considering the possibility of high phytoplankton concentrations in storage reservoirs further reduced the estimated system reliability. Possible changes in land use and agricultural practices could exacerbate (in the case of agricultural intensification) or mitigate (in the case of more sensitive agricultural practices and improved waste water treatment) the risk of water quality impacts on the reliability of public water supplies. However, the mitigation effect of pollution abatement was found to be small when compared to the projected effect of climate change and was not as significant when reservoir water quality was also included in the reliability analysis.

Building upon the work of Hashimoto et al. (1982) and subsequently Borgomeo et al. (2014), our method has focused upon the frequency and severity of restrictions on water use as an outcome measure of the performance of water resource systems. We have extended previous work on risk-based analysis of water resource systems to incorporate water-quality related restrictions on public water supplies. In doing so, we have had to construct a coupled simulation framework that deals with the dynamic interactions between water quality and quantity in the context of active human management of the water resource system. We regard this innovation as being a next step in the development of risk-based methods for the sustainable management of coupled human and natural systems.

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