Adaptive water resources planning to manage future risks to London's water supply

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Abstract

Water resource management in the 21st Century is challenged by climate change impacts, increases in consumer demand, and environmental degradation. In the UK, water planners must secure long-term public water supply whilst facing increased exposure to climate-related hazards from increased aridity and uncertainties in future precipitation. It is widely accepted that to overcome such risks, water agencies must manage water demand, reduce the amount of water that is wasted through leakage, modify operational and regulatory policies, and build new supply infrastructure to increase water system capacity. However, significant uncertainties complicate adaptation decisions.

This thesis presents three novel risk-based frameworks that address some of the challenges surrounding adaptability and uncertainty in 21st Century water resource planning. The aims of the thesis are: (i) to develop an adaptive risk-based planning methodology which is designed to cope with uncertain climate and demand projections by identifying decision rules that inform adaptive water resources planning decisions; (ii) to investigate the vulnerability of water management planning options to heterogeneous patterns of water use and spatially connected extreme climate events with characteristics not represented in the historical record, and examine how management decisions can be informed by extensive stress testing; and, (iii) to better incorporate river ecosystem health in water resource planning decisions, so regulatory decisions do a better job at preserving the aquatic environment in changing climatic conditions.

The research presented in this thesis uses state of the art hydro-climatic data and water demand projections alongside simulation and optimization-based methods to achieve the aims described above. The proposed planning frameworks target uncertainties

inherent to the London water supply system in the Thames Basin, England, but have been designed so that they can also be applied to regions facing similar planning uncertainties.

This thesis demonstrates the value of systematically planning for hydro-climatic, environmental, and socio-demographic uncertainties. The findings suggest that water resources planning under uncertainty can be enhanced through monitoring of observable features of the water system, and by learning from simulation-based vulnerability analyses of proposed water management options and regulatory policies. Results from the case study investigations indicate that significant climate- and demand-related risks threaten water security in London and the wider Thames region. Without adaptation, water restrictions to domestic water users are projected to increase in frequency and severity throughout the 21st Century. For example, by 2099 the probability of severe water restrictions occurring on any given day in the Thames Basin are calculated to increase by 266% compared to the baseline period (1975-2000). Meteorological and hydrological droughts are also predicted to become more spatially extensive, affecting multiple water supply systems in Southern England and threatening the yield of existing infrastructure. Lastly, aquatic health is shown to deteriorate as water supply pressures increase.

Overall, the results demonstrate how future risks in the Thames Basin can be navigated by adopting the quantitative methods presented in this thesis. By following a rule-based planning approach, water managers are able to make better informed investment decisions and could reduce the costs of water use restrictions by up to 24% over the next 60 years. Implementation of a new water transfer from the Severn Basin to the Thames is likely to increase the resilience of Thames Water's water supply system to severe drought events, but only if adequate water storage is made available in the receiving region. Finally, modification of existing water withdrawal policies is necessary to maintain historically observed macroinvertebrate health (LIFE Scores) into the future. This thesis

shows that increases to minimum required flow constraints along the River Lee, a catchment in the Thames Basin, could result in 21.3% improvements in LIFE Scores by the end of the century compared to the current policy.

Publications

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1 Introduction

1.1 Background and rationale

Loucks et al. stated in 2005 that "water resource systems planning and management issues are rarely simple" (Loucks et al. 2005, p. ix). 15 years later, this statement remains true, with parts of the world facing water supply crises at local, regional and national scales (Liu et al. 2017). For example, in 2017 World Health Organization and UNICEF reported that at the household level, 30% of the world's population lacked access to a safely managed drinking water source, and only 59% received their drinking water from a piped source (WHO & UNICEF, 2019).

Climate change, increases in consumer demand, and environmental degradation have significantly impacted water resources globally (Grafton, 2017; Liu et al. 2017; Vörösmarty et al. 2010), with existing water supply infrastructures, operations, and regulation failing to meet demand and environmental requirements under 21st Century conditions. Moreover, mismanagement during extreme climatic events has intensified water stress, leading to disconnected river networks and disrupted food webs (Power et al. 2015), and reduced streamflow (Barnett et al. 2008). The importance of careful planning for disruptions to water supply systems exist globally, with water managers in Australia (Aghakouchak et al. 2014; Mortazavi-Naeini et al. 2014), western parts of the US (AghaKouchak et al. 2015), Egypt (Wheeler et al. 2018), Southern England (Borgomeo et al. 2018; Matrosov et al. 2015), and the Netherlands (Haasnoot et al. 2015) facing issues related to climate change, increased demand for water, operational scheduling, and policy reform. In summary, decisions concerning water resources have never been more complicated.

Public water resource system planning and management principally examines portfolios of proposed changes to the water system that aim to maintain the security of water supply into the future. Water planners typically evaluate capacity expansion options (new infrastructure), water demand management schemes, and operational policies that will help to alleviate stress to the water supply system. Traditional approaches to water resource planning use historical datasets to examine adaptation portfolios, simulating system response to the conditions observed in the historic record. A cost-benefit analysis (CBA) of the adaptation portfolios helps to select the most economically viable solutions for the water planning problem. However, industry experts and academics acknowledge that incorporating spatially heterogeneous sources of uncertainty and competing objective values into CBA remains a significant challenge for water planners (Brown, 2010). Furthermore, methodologies that use historical datasets to evaluate water planning portfolios are considered insufficient when planning for a future with non-stationary climatic conditions (Milly et al. 2008), and increased anthropogenic impacts to water systems (Watts et al. 2015).

The need for updated and expanded water management practices has been widely discussed in the water planning and management literature. For example, Matrosov et al. (2013) find problems with using stationarity assumptions in human-water systems when statistical distributions of future conditions are poorly known. Likewise, Nazemi et al. (2013) state that analyses of uncertainties in current climate and hydrological models are outdated, providing only a limited insight into dynamic system response. Hall et al. (2012) call for portfolio assessments using probabilistic risk-based scenarios of climate change and hydrological drought that simultaneously account for internal and external uncertainties in model projections. Meanwhile, Stakhiv (2011) suggest a reevaluation of

decision rules and the key principles used in traditional water resources management, with new methodologies accounting for highly uncertain future climate trajectories.

Notable progress has been made in the last decade to cope with the uncertainties afflicting water resource planning and management in the 21st Century. Existing deterministic planning approaches using historical observations have been transformed to incorporate non-stationary climate ensembles (Borgomeo et al. 2014), stochastic climate analyses (Brown & Wilby, 2012), and socio-economic demand scenarios (Hunt & Wade, 2016). New methods have enabled assessments of adaptation portfolio robustness to climatic conditions that exhibit characteristics outside the envelope of historical variability (Nazemi et al. 2013), and allowed evaluation of water resource plans against performance criteria such as tolerable risk and investment costs (Borgomeo et al. 2016). In particular, development of risk-based approaches in water resource planning and management have enhanced decision making frameworks by recognising that adaptation in water resource systems is multi-dimensional. Unlike former methods that rely on cost-benefit and least-cost analyses, risk-based methodologies highlight the trade-off in costs of adaptation options against measures of risk important to the stakeholders involved in the decision-making process. Within water resource planning, risk could be represented by the frequency of water use restrictions (Borgomeo et al. 2016), ecological performance metrics (Poff et al. 2016), or the incidence of catastrophic flood events (Quinn et al. 2017). Using simulation techniques, measures of risk can be used effectively as indicators of system performance under uncertain future conditions, providing a probabilistic metric directly linked to stakeholder objectives. This is particularly useful for water planners who must consider multiple objectives when developing long-term plans.

Despite significant advances in techniques, methodological challenges still exist within the water resources planning literature. The dynamic representation of decision

making in simulated water resource planning is a prominent issue, limiting the applicability of decision making frameworks to real world problems (Brown et al. 2015). Moreover, many existing adaptation approaches rely on water agencies to commit to 'lumpy' long-term plans without knowing that the chosen plan is ideal for the actual future realised (Haasnoot et al. 2013). This is particularly risky for planning water supplies that are highly vulnerable to future uncertainties, often involving large capital commitments and significant social consequences. Building on this knowledge, future water resource systems planning and management should aim to incorporate decision making techniques that respond to anticipated water scarcity and observed conditions as they are realised in real time.

Additional scope exists to improve upon current quantitative methods that test proposed water supply infrastructure and operational policies to uncertain future conditions. As awareness of climate change grows, it is becoming increasingly apparent that historical observations are insufficient to inform water resource planning. This is particularly evident in regions facing spatially extensive and increasingly severe drought events spanning multiple water supply systems, each with different patterns of water use. In order to identify adaptation actions that reduce the risk of water system failure under large spatially dependent droughts, water resource modelling platforms must use state of the art climate and hydrological information containing climatic events not present in the historical record. The climate and hydrological information can be used to stress-test adaptation actions that may be vulnerable to spatially heterogeneous extreme synthetic climate events (Connell-Buck et al. 2011; Dobson et al. 2020; Watts et al. 2015), and identify management policies that help navigate increasing water demand pressures.

Opportunity also exists to develop water resource planning frameworks that explicitly recognise the risk of climate change, water demand growth, and adaptation

actions on the aquatic environment (Acreman et al. 2014; Stoffels et al. 2018). Responses to increased risk of ecosystem damage have traditionally involved the implementation of precautionary regulatory thresholds (Klaar et al. 2014), which set limits and restrict the withdrawal of water from surface and groundwater supplies during periods of low flow. Yet, existing approaches fail to reflect the dynamism of ecosystems under shifting environmental regimes (Arthington et al. 2018), or to rigorously predict changes in ecosystem health in a non-stationary world (Poff, 2018). Future research should therefore focus on developing decision making tools that are capable of designing new water regulation policies that balance emerging trade-offs between water supply and environmental degradation under uncertain future scenarios.

In light of the discussion above, this thesis develops and applies three risk-based frameworks that address key challenges inherent to water resource planning and management problems in the 21st Century. Each investigation explores trade-offs between adaptation and a measurement of risk, with the aim of using the information learned over time to inform both short- and long-term decision making in water resource planning. The techniques presented in this thesis target uncertainties inherent to the Thames Basin and London water supply system. Across the UK, water planners must secure long-term public water supply whilst facing increased exposure to climate-related risks such as amplified drought covariance (Rahiz & New, 2013), and decreased water availability (HR Wallingford, 2015). It is widely accepted that to overcome such risks, water agencies must adapt existing water infrastructure, modify operational policies, and build new supply infrastructure (Hall et al. 2012). Within the Thames water supply system, adaptation options may include (but are not limited to) increases in river withdrawals, amendment of reservoir operating agreements, and construction of new water transfers and desalination plants.

1.2 Aims and objectives

This doctoral thesis aims to innovate and operationalise current water resource planning methodologies by advancing risk-based approaches to decision making. The techniques presented are designed to target specific uncertainties inherent to water resource systems planning and management, tackling issues arising from climate change, population growth, and environmental degradation. The thesis seeks to illustrate the applicability of the proposed approaches, using the London urban water system and surrounding areas as a demonstrative case study. The following objectives were identified to achieve this aim:

i. Develop an adaptive risk-based planning methodology which uses uncertain climate and demand projections to identify optimal decision rules that inform water resources planning decisions;
ii. Investigate the vulnerability of water management planning options to spatially heterogeneous patterns of water demand and extreme synthetic climate events with characteristics not represented in the historical record, and examine how management decisions can be informed by extensive stress testing;
iii. Evaluate the role of river ecosystem health in informing water resource planning decisions under regulation and climate change uncertainties.

1.3 Case study

This doctoral research presents risk-based methods to aid water resource planning decisions in the face of uncertain changes in water demand and supply. The methods presented inform water resource planning problems and allow planners to examine important trade-offs between adaptation cost, flexibility, resilience, and level of service to water users. The Thames Water supply system (Thames Basin, England) is used to demonstrate the proposed methods. This case study area is ideal for the research presented

in this thesis because water management decisions in the Thames Basin face significant challenges from climate change, population growth, environmental degradation, and uncertain regulation reforms.

The importance of testing potential infrastructure portfolios in the Thames Basin against future global climate change scenarios is well evidenced in the decision-making literature. For example, Huskova et al. (2016) reveal that adaptation portfolios for the Thames system have a high chance of failing under future scenarios. Likewise, Matrosov et al. (2013) show that portfolios identified through info-gap and robust decision making frameworks are considered robust, but not optimal, solutions to the Thames Basin water planning problem.

In the most recent round of Water Resources Management Planning (WRMP), large investments in current and new water supply infrastructure were considered by Thames Water Ltd to overcome projected declines in deployable output (Thames Water, 2019a). WRMP is conducted in compliance with the regulations set by the water authority OFWAT. All UK water companies must publish WRMP reports every 5 years, outlining a "secure and sustainable set of options to supply [your] customers with water over the long-term" (Environment Agency, 2018, p.1). The most recent plans were published in 2019 and contain an executive summary of a company's business plan, reviews of baseline supply-demand balance, feasible options for future investment, and analysis of climate change risks. Each plan refers to Water Resource Zones (WRZs), defined as the "the area within which the abstraction and distribution of supply to meet demand is largely self-contained" (Environment Agency, 2018).

Thames Water Ltd supplies water to six WRZs (**Figure 1.1**). The largest, London WRZ, supplies water to 3.7 million households in London (Thames Water, 2019a). In Thames Water's WRMP19, concern is expressed over London WRZ's supply and demand

complexity, with planning challenges arising from limited resilience of the current water supply system to drought, climate change, water quality issues, and amendments to withdrawal regulations (termed sustainability reductions). In 2019, a strategic analysis of risk to customer service indicated high risk to customers located in the London WRZ, signifying that (i) customer service will be highly affected by future supply and demand side risks, and (ii) investment to mitigate risks will be costly and contentious (Thames Water, 2019b). To overcome these issues, Thames Water's WRMP19 identified a best value demand-supply appraisal programme for planning periods to 2030, 2037 and 2080. A selection of the demand management and capacity expansion options evaluated in Thames Water's WRMP19 are used in the research presented in **Chapters 4**, **5**, and **6**.

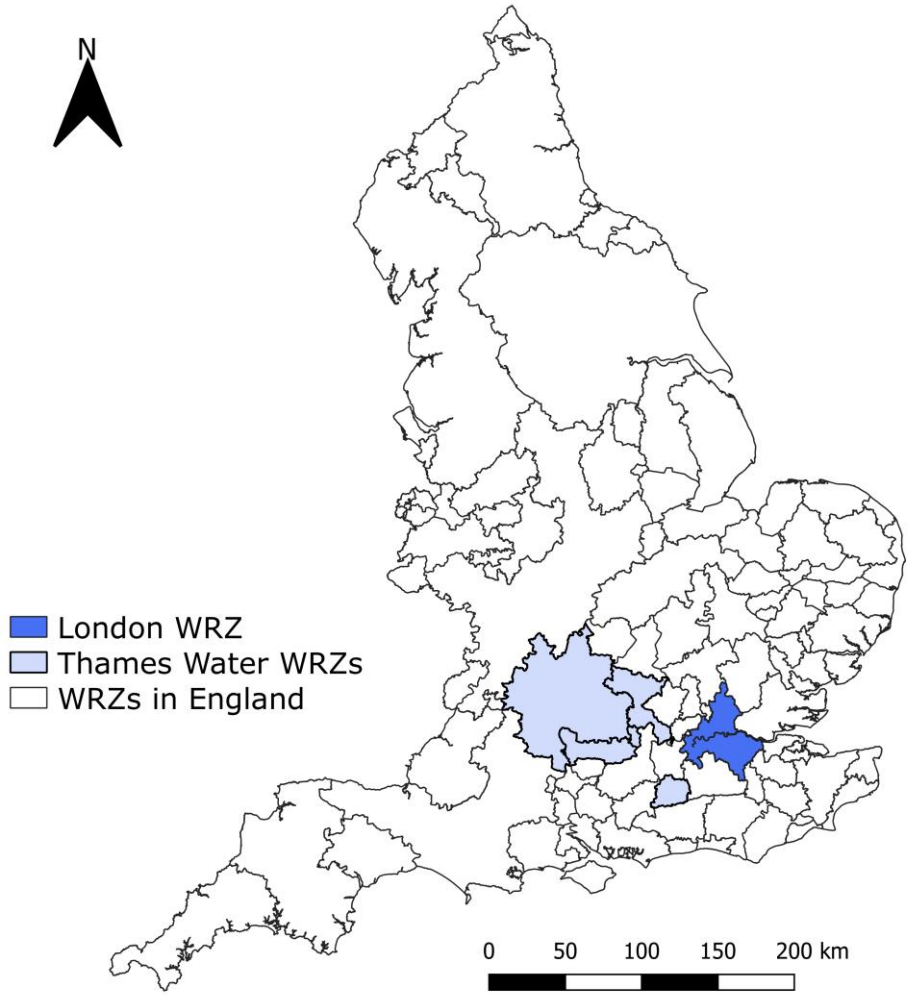


Figure 1.1. Case study area. Figure highlights Thames Water water resource zones, including the London water resource zone.

1.4 Thesis structure

This thesis is comprised of seven chapters and follows the guidelines of an article-based thesis, as outlined by the University of Oxford's School of Geography and the Environment. **Chapter 2** presents a comprehensive review of key themes in the current water resources and planning literature. The chapter features critical discussion of the methodologies used to deal with uncertainty in water systems decision making. This chapter provides context for the theoretical and methodological approaches presented in

Chapters 4, **5**, and **6**, and justifies their necessity to achieve the aims outlined in **Section 1.2**.

Chapter 3 provides an overview of the data and modelling tools used in the thesis research. Within the chapter, the data and modelling tools are compared to equivalent resources that exist within the discipline.

Chapter 4 builds on existing approaches to water resource planning and management. Instead of using cost-benefit analysis to generate fixed infrastructure plans, the chapter presents a new framework for identifying optimal rule-based strategies. The new strategies deliver better outcomes at lower costs by allowing infrastructure investments to be made flexibly, according to decision rules based on observable climate and demand metrics. The four-stage framework uses a multi-objective evolutionary algorithm to search for and identify combinations of decision rules that govern if, when, and what infrastructure options should be built into the water system. The research goes beyond current methods of long-term water planning under uncertainty to create planning strategies that adapt as demographic and climatic changes are realised over time.

Chapter 5 presents an in-depth analysis of the resilience of specific infrastructure options evaluated in **Chapter 4** to extreme spatially extensive drought events. The chapter illustrates the value of using large ensembles of climate change driven future flows in water resource planning, especially in evaluations of infrastructure options reliant on sharing water between regions vulnerable to spatially coherent droughts. The chapter presents a simulation-based framework that may be used in conjunction with the risk-based method outlined in **Chapter 4** to inform long-term adaptation decisions. Together, the two chapters illustrate the important trade-offs between customer service, climate related risk, and the cost of adaptation.

While the methods presented in **Chapters 4** and **5** overcome climate and demand related uncertainty issues, they do not consider future changes in water regulation and the impact of adaptation on river ecosystem health. Assumptions that regulatory constraints will remain constant into the future may lead to an over estimation of water supply availability from surface water, and therefore produce riskier plans than previously anticipated. To overcome uncertainty arising from regulatory constraints, **Chapter 6** presents a methodology to identify thresholds of river withdrawal limits that systematically trade-off water supply against damage to the aquatic environment. The proposed framework is used to test the vulnerability of surface water supply to regulatory changes, and offers a way to transition from blunt regulation regimes typical of UK water policy to an arrangement of joint ecosystem and water supply resilience.

Chapter 7 presents the principal conclusions of the thesis. Within the chapter, research contributions and practical applications are described, followed by suggestions for future research. The thesis concludes with closing remarks.

2 Review of water resource systems planning and management

Water resources systems analysis is widespread within academic literature and practice. This chapter provides a comprehensive, but by no means exhaustive, review of key themes that exist within the discipline, and describes the methodologies used to identify adaptation actions in the face of uncertainties inherent to multi-objective water system planning.

2.1 Water system representation, modelling, and multi-objective planning

A water resources system is composed of "connected hydrologic, infrastructure, ecologic, and human processes that involve water" (Brown et al. 2015, p. 6111). Computer-based water system models attempt to best represent features of the water resources system, based on assumptions and approximations of physical, climatological, hydrological, social, and political processes. It is widely recognised that water resource systems models are highly simplified versions of real-world systems. For this reason, water systems models should be built with the decision problem and solutions at the forefront of the modelling process (Kwakkel et al. 2016). Loucks et al. (2005) list five reasons for when modelling is appropriate for solving water resources planning and management problems:

i. The modelling objectives are well defined and informed by stakeholder dialogue;
ii. A solution to the planning problem is not clear (although many competing solutions may exist);
iii. Features of the water system to be modelled can be represented by mathematical notation;

iv. Desired model outputs are better estimated using models than through the use of real-world data;

v. Model parameters can be estimated from existing data.

The research presented in this thesis uses simulation models to quantify the impact of changing climatic, social and environmental conditions on water supply, and evaluate how adaptation decisions can mitigate this impact. Simulation models have grown in both popularity and complexity, evolving from models that assess bulk water supply and balance estimates to tools that evaluate key metrics of system performance under changing conditions (Borgomeo et al. 2018). Systems analysis models built with network-flow programming (NFP) deal with issues associated with increased system intricacy, using a network of interconnected nodes and arcs to move water through the supply system. A simple systems model will contain: (i) nodes to represent river and groundwater inflows, reservoir storage, public and non-public water demand, and waste (model outflows), and; (ii) arcs to represent flow pathways, such as rivers, canals and pipelines. Constraints can be assigned to individual nodes or arcs, to ensure that environmental demands and regulatory rules are met.

Algebraic equations represent key features of the water system, such as design variables and operating policies. Within the model, design variables can include reservoir storage (active and initial capacities), characteristics of supply infrastructure (pumping capacities, wastewater treatment efficiencies, pipe proportions), and hydrological features (levee height, river and canal dimensions). Operating policies signify the rules policing movement of water in the system, such as reservoir releases, water allocation, and regulatory constraints. During model development, parameter variables are examined to identify values that best replicate conditions observed in the real system. Sensitivity analyses (SA) can be used at this stage to examine a range of values for different

parameters and estimate the impact of changing values on model output (Pianosi et al. 2016). SA can also be used to examine the effect of contextual uncertainty on model output, which commonly arises from poor definition of modelling boundaries within interconnected water supply systems (Dobson et al. 2019).

Together with stakeholders, water planners must specify modelling objectives and planning outcomes. Water resource planning objectives are usually aligned with a measure of system performance, such as: minimising economic operating and capital costs (Kingsborough et al. 2016); minimising environmental degradation (Poff et al. 2016); increasing system robustness to future climatic and hydrological conditions (Jeuland & Whittington, 2014); minimising greenhouse gas (GHG) emissions (Paton et al. 2014); increasing social livelihood (Hurford et al. 2014), and; minimising financial risk (Zeff et al. 2014). Importantly, objective choice may introduce additional uncertainty to the planning problem (Quinn et al. 2017). Care should therefore be taken when identifying objectives in the problem formulation and system model development phase. This thesis explores trade-offs between multiple competing planning objectives in an uncertain future, including the cost of adaptation, security of water supply, and aquatic health. As Cui & Kuczera (2005) argue, multi-objective planning is paramount to satisfying the objectives and risk tolerances of multiple users within water headwork systems because each system component is influenced by competing purposes. Reservoir system operation is characteristically multi-objective as it must meet ecological streamflow targets and target levels of storage, whilst balancing upstream and downstream flow during extreme climate events (Kim et al. 2006; Steinschneider et al. 2014). Likewise, long-term water infrastructure planning inevitably involves trade-offs between financial objectives and customer service (Borgomeo et al. 2016), robustness to future climate uncertainties (Borgomeo et al. 2018), and the social burden of drought emergencies (Mortazavi-Naeini

et al. 2014). By framing the water resources planning problem as multi-objective, water planners can visualise emerging trade-offs in the multi-objective space and identify adaptation solutions that balance the competing needs of stakeholders involved in the planning process.

Upon defining and integrating key features of the water system in the system model, and specifying the vector of objectives (or objective functions) to satisfy, the simulation model can be used to test prospective adaptation options. The models can be run on discrete time-steps (typically daily, monthly or yearly) or for discrete events (i.e. drought periods), using non-stationary exogenous forcing inputs from emissions driven climate sequences, modelled hydrological flows, and domestic, industrial, and agricultural water demand projections. Input data are subject to multiple uncertainties, which are discussed in the next section. When defining the planning problem, it is important to identify the most suitable time-frame to be simulated (Horne et al. 2016). Shorter time-steps (days, weeks) are more suited to operational and regulatory planning problems that require decisions to be made on short notice (Matrosov et al. 2013; Wu et al. 2015). Problems that evaluate long-term planning decisions are likely to be run on coarser time-steps (months, seasons, years), such as infrastructure capacity expansion planning (Borgomeo et al. 2016), and flood risk strategising (Woodward et al. 2014). Aggregation of time-steps is important to manage the costs associated with long computer run times and high computational intensity. However, care needs to be taken to ensure that important day-to-day intricacies of the water system being modelled are not lost. If available, high performance and parallel computing can overcome this issue, allowing long-term planning problems to be evaluated at monthly, and sometimes daily, time-steps (Brown et al. 2015; Cui, 2003).

2.2 Data, modelling processes, and uncertainty characterisation

As described above, simulation tools and optimization methods can be used to identify suitable adaptation options for the planning problem. Yet specifying the conditions under which to run the water system model can be difficult when the future remains uncertain. Because the modelling tools used in water resource planning conceptualise reality, they are biased approximations of what each modeller considers the most important features of the system (Wagener & Gupta, 2005). For this reason, uncertainties exist at every stage in the water planning process, cascading from greenhouse gas driven climate projections, to rainfall-runoff modelling, to human-environment systems models (Wilby & Dessai, 2010). It is imperative to recognise this uncertainty when conducting impact assessments and solving water planning problems at local, regional or continental scales (Archfield et al. 2015).

Uncertainties affecting simulation-based investigations are commonly characterised as aleatory, epistemic, semantic, or ontological (Beven, 2016). Aleatory uncertainties arise from random variability of processes in the water system, and are assumed to be irreducible. In modelling experiments, sources of aleatory uncertainty are typically represented by stationary random distributions. In contrast, epistemic uncertainty is attributed to a lack of knowledge about system dynamics, forcing data, expected behaviour, and disinformation. Whilst epistemic uncertainties are reducible in practice, they are difficult to represent and can complicate interpretation of modelling outputs. Semantic uncertainty is attributed to differences in terminology across the discipline, whilst ontological uncertainty stems from diverse philosophies of uncertainty representation.

Water resource planning frameworks commonly target epistemic and aleatory uncertainties arising from (i) representation of greenhouse gas emissions and forcing, (ii)

climate modelling, (iii) regional downscaling, (vi) hydrologic modelling, (v) water system representation, and (vi) the initial conditions defined at the start of modelling experiments. These sources of uncertainty are often described a ‘exogenous’ uncertainties, as they stem from uncertainty in forcing, model structure and parameterisation (Herman et al. 2020).

Uncertainty generated by human behaviour and environmental processes has received less attention in the water planning literature (Brown et al. 2015), despite evidence indicating that these sources of uncertainty may equal or exceed the impact of climate change uncertainty in water resource problems (Fant et al. 2016). Sources of human-environmental uncertainty include (i) changes in social and economic behaviour, (ii) indirect impacts of climate and hydrologic change, (iii) institutional change, (iv) policy actions, and (v) long-term environmental changes. These sources of uncertainty are commonly referred to as ‘endogenous’ (Erfani et al. 2020).

The following sub-sections elaborate further on the sources of uncertainty common to individual stages of water resource planning frameworks. Each section describes the modelling processes, assumptions, and associated uncertainties to be considered when designing water resource plans.

2.2.1 Climate modelling, emissions, and regional downscaling

Water resource planning often requires projections of future climate change derived from Global Climate Models (GCMs). GCMs are numerical representations of the physical processes that occur in the ocean and atmosphere, governed by fundamental laws of physics such as the conservation of mass, energy and momentum. GCMs divide the atmosphere or ocean into a grid with a typical spacing of 200 to 300km in the horizontal and 30 to 50km in the vertical; giving roughly 30 grid layers between the surface and top of the atmosphere (Räisänen, 2007). Coupled AOGCMs automatically compute fast

feedback processes (water vapour, clouds and seasonal snow, the uptake of heat by the oceans etc.), to directly simulate winds, ocean currents and other features of global circulation. Computational limitations and the large grid spacing result in parameterisation of small sub-grid scale processes. Changes in climate properties are estimated by comparing a simulated future climate with a simulated present-day climate, using the same model or ensemble for each projection to cancel any biases in model configuration.

Uncertainty manifests in several ways in climate change modelling. Firstly, considerable uncertainty exists in projections of 21st Century emissions; particularly in projections of the second half of the century (Murphy et al. 2009). The IPCC Special Report on Emissions Scenarios (SRES) and Representative Concentration Pathways (RCPs) were designed to encapsulate the possible range of future emissions, quantifying different magnitudes and severity of change in greenhouse gas and air pollutant concentrations (Intergovernmental Panel on Climate Change, 2013). Today, RCPs are commonly used in climate impact assessments and water supply planning (Akbari-Alashti et al. 2018; Prudhomme et al. 2014; Robinson & Herman, 2019). Four RCPs are defined, corresponding to different levels of radiative forcing that could emerge as a consequence of future human activities and socio-economic scenarios. RCPs are not classified as equally likely, with the weighting of each scenario proving controversial (Katz, 2002; Kundzewicz et al. 2018). The choice of RCP scenario, in addition to the underlying assumptions made about emissions forcing, can add considerable uncertainty to climate impact assessments.

Secondly, GCMs with parameterised sub-gridscale processes are inherently uncertain. Using a 53-member ensemble of the HadAM3 model with varying parameters, Murphy et al. (2004) illustrate the effects of parameterisation on model performance. Significant disagreement arises between projections of precipitation and temperature, with

temperature showing the greatest skill. Further uncertainty arises from the data required to run and calibrate models, which is often incomplete and inaccurate due to errors in data detection and measurement. Errors at the smallest scale could affect GCM projections at the synoptic scale after 2 days of run time, and then at the global scale after 14 days. This is most relevant to direct observations of precipitation, which are difficult to measure accurately and efficiently (Trenberth, 2011).

Thirdly, uncertainty arises from downscaling methods to represent global climate change at smaller regional scales. Wilby & Harris (2006) propose a probabilistic framework to measure uncertainty in low-flow scenarios for the River Thames, using four GCMs, two SRES scenarios, two statistical downscaling techniques, and two hydrological models with two sets of hydrological parameters. The uncertainty of each component in a 2080 low flow projection is quantified using Monte Carlo analysis, which assigns performance weights according to an index of reliability, a flow reproduction measure, and the Nash-Sutcliffe efficiency criterion of hydrological model performance. Results reveal that inter-annual variations in climate change scenarios and statistical downscaling contribute the most uncertainty compared to model parameterisation and SRES scenario. To avoid issues of downscaling, Dessai & Hulme (2007) use a combination of GCM and regional climate model (RCM) projections to robustly model the impacts of climate change on a water system in the East of England. Unlike other top-down approaches that operate on the global to local scale, the study conducts a local sensitivity analysis of uncertainty. Adaptation options are first identified, then exposed to an impact model run with an RCM. This produces regional climate change probability density functions (PDFs), which are then exposed to SRES A2 and B2 emissions scenarios. The results are scaled by a global temperature change PDF, before being input in the energy-balance model MAGICC. MAGICC allows uncertainty analysis to be performed on GHG emissions, climate

sensitivity, aerosol forcing, carbon cycle, and ocean diffusivity. The bottom-up method exhibited by Dessai & Hulme (2007) permits examination of individual parameter uncertainty at each stage of the framework while other parameters are kept constant. Moreover, the uncertainty created by GCM projections is omitted from the PDFs until the last stage, which means that uncertainty of the adaptation options under RCM projections can be assessed beforehand.

2.2.2 Hydrological modelling, spatial variability, and parameterisation

Hydrological models, or rainfall-runoff models, have been widely employed for water resources assessments and climate impact studies, transforming output from climate modelling platforms and information on catchment properties into time series of river flows and groundwater levels. Hydrological modelling is considered a necessary tool to water resources planning and management as it helps represent spatial and temporal variations of surface water supplies in simulations of water supply systems (Coxon et al. 2019). Furthermore, simulation and prediction of river flows extending beyond the range of observed variability are essential in the development of adaptation plans aiming to build the resilience of water supply systems to hydrological extremes (Wagener et al. 2010).

In hydrological modelling, the hydrological behaviour of a river basin or catchment is conceptualised as a series of spatially distributed water, energy, and vegetation processes, each of which are represented as mathematical equations. Models can be classified as empirical, conceptual, or physically based, depending on input, parameter choice, and the physical principles represented within the model. Over the last half a century, advancements in hydrological modelling techniques have enhanced the simulation and prediction of surface water, groundwater, evaporation, transpiration, and soil moisture. Improved representation and evaluation of complex drivers of catchment

behaviour (Ewen et al. 2013; Gao et al. 2017) and upgraded data storage and model vectorisation features (Metcalfe et al. 2015) have benefitted the discipline considerably.

Recently, research has focussed hydrological modelling issues associated with heterogeneous hydrological response and changing landscape connectivity. Of note is the work by Coxon et al. (2019), who present a spatially flexible modelling framework to simulate hydrologic flows for catchments of varying spatial scale and hydrologic connectivity. The modelling framework, DECIPHeR (Dynamic fluxEs and ConnectIvity for Predictions of HydRology), uses digital terrain analysis to represent the varying spatial topology of a modelled catchment. To avoid the high computational costs associated with high resolution modelling, DECIPHeR defines hillslope and riverine morphology as a series of individual hydrological response units (HRUs), which group features of the landscape with similar morphological characteristics. The HRUs successfully aid the simulation of complex river basins with spatially heterogeneous features, which may have otherwise been overlooked in hydrological models with a fixed representation of spatial variability. As Coxon et al. (2019) state, DECIPHeR's methodological advancement is transformative for water resource assessments of systems facing water challenges from spatially heterogeneous hydrological risks.

Despite the developments described above, hydrological models remain limited by parameterisation, the loss of direct physical interpretation, and measurability (Wagener & Gupta, 2005). Renard et al. (2010) identify four discrete sources of uncertainty in hydrologic modelling: (i) input uncertainty; (ii) output uncertainty; (iii) structural uncertainty, or model uncertainty; and, (iv) parametric uncertainty. Models can be calibrated to identify the best behavioural set of parameters in an attempt to bring model simulated input-output behaviour close to processes observed in the field. This requires specific localised data to account for heterogeneity in the landscape. Inhomogeneous

geology, relief, land use, and vegetation cover can all contribute to increased uncertainty in hydrological simulations, especially if the model has not been calibrated correctly.

Early assessments of hydrologic model uncertainty were conducted by comparing observed and predicted hydrographs (Beven, 1987; Beven et al. 1984; Lamb et al. 1997). As computing power has increased, the ability to assess parameter and structural uncertainty has improved considerably. For instance, Ajami et al. (2007) demonstrate the importance of considering different forms of hydrologic uncertainty in order to avoid biased and corrupted parameter estimates. Using the Integrated Bayesian Uncertainty Estimator (IBUNE), they distinguish between parameter, input and structural uncertainty in the Sacramento Soil Moisture Accounting (SAC-SMA) model, the soil water balance model (SWB), and the hydrologic model (HYMOD). Meanwhile, McMillan et al. (2010) use a Monte Carlo Markov Chain (MCMC) framework to systematically assess and quantify uncertainty in discharge measurements. Their study emphasises the need to consider uncertainty introduced by misread gaugings, assumptions of stage-discharge relationship, and cross-section change due to vegetation growth and/or bed movement.

The Generalized Likelihood Uncertainty Estimation (GLUE) framework has also been used to quantify uncertainty within hydrological modelling (Cameron 2007; Lin et al. 2010; Bastola et al. 2011; Liu et al. 2012). GLUE compares model predictions and observations of an event, and can be coupled with other calibration techniques such as fuzzy rule-based calibration and MCMC (Aronica et al. 1998). The methodology is based on Bayesian analysis, using a prior distribution of parameter values to generate random sets for use in each behavioural model using MC simulation. Consistent with previous studies described here, model results are tested against performance measures and modelling residuals. Assigned likelihood measures for acceptable behavioural models are

used to produce weighted predictions, uncertainty estimates, and prediction limits of the simulation (Beven, 2012).

The work by Coxon et al. (2019) also adopts Monte Carlo simulation to explore parametric model uncertainty in the DECIPHeR modelling framework, using 10,000 widely-sampled parameter sets to simulate daily time series of discharge for 1366 locations across Great Britain. Results from the investigation helped to identify the best parameter sets, according to four evaluation metrics, for individual catchments in Britain, and have since been used by Dobson et al. (2020) to examine the spatial dynamics of droughts and water scarcity across England and Wales. Future work is expected to explore the hydrological uncertainty introduced to water resource planning when parameter sets that prioritise simulation of low flows are used instead of the 'best' parameter sets.

2.2.3 Water demand, population change, and per capita consumption

Water demand is traditionally characterised as industrial, agricultural, energy, or domestic (municipal). This thesis principally focusses on domestic water demand, which makes up 58% of surface water withdrawals in England (Environment Agency, 2013b). In the most simplistic representation of domestic water demand, demand growth is either assumed to be known (Erfani et al. 2018), or expected to follow one of multiple independent scenarios (Jeuland & Whittington, 2014). In reality, domestic demand is a function of population, per capita demand, and commercial and industrial demand (Beh et al. 2014). The drivers of demand can vary between regions, depending on patterns of water use and allocation (Hall et al. 2019).

For areas experiencing urbanization and migration, population growth has intensified pressures on existing water supply systems, by increasing demand requirements for both public and non-public water use. Global-scale studies have shown that by 2050,

uncertainty in population growth could have a larger impact on water resource systems than climate change uncertainty (Sapkota et al. 2015; Schlosser et al. 2014; Vörösmarty et al. 2000). Within the planning literature, uncertainty in population projections is most commonly represented by scenarios of annual growth rates, derived from historical data, demographic models and forecasts (Beh et al. 2014; Borgomeo et al. 2014; Borgomeo et al. 2015; Hall et al. 2019). Annual growth rates are usually scalar and determine the magnitude of population growth year on year. However, the growth models commonly assume that the population growth rate does not change with time. To overcome this limitation, Fletcher et al. (2017) use Monte Carlo simulation to randomly choose population growth paths for individual water planning stages within simulation runs. This ensures that adaptation infrastructure is extensively tested against a wide range of non-linear population change scenarios.

Demand is also determined by per capita consumption, or PCC. PCC specifies the average water consumed per capita and is often aggregated to demand per household. As with population growth, uncertainty in PCC can be represented by scenarios of scaled annual PCC changes (Borgomeo et al. 2018; Ives et al. 2018). Within PCC forecasting, uncertainty arises from two main sources. As above, the first source of uncertainty comes from pre-specifying the direction of PCC change. Linear forecasts of PCC can be problematic for water systems with demand-side management schemes in place, which aim to reduce water demand through ‘smart-use’ technologies and financial incentives (Lambert, 2015). Customer response to demand management schemes can result in non-linear patterns of water use that are difficult to capture in traditional water system modelling frameworks. This issue is closely linked to the second source of uncertainty, which arises from assumptions of static domestic water use patterns. Although it is possible to predict the changing nature of demand in heightened drought conditions, it is

difficult to decouple consumptive use from the amount of precipitation and river flow in a catchment. The notion that water consumption does not change intra-annually ignores the influence of day-to-day and monthly temperature fluctuations and weather patterns on water use (Parker & Wilby, 2013). To overcome this, Chung et al. (2009) use correlated uncertainties in demand and supply to design a reliable 15-year planning portfolio for a hypothetical municipal water supply system. In the study, global optimization is used to solve a non-linear problem of correlated uncertainties in supply and demand, highlighting key issues of using deterministic forecasts of water use.

Unforeseen changes in demand as a consequence of adaptation action also introduce endogenous uncertainty to the water planning problem, with patterns of demand evolving as decisions are made in real time (Erfani et al. 2020). For example, Di Baldassarre et al. (2018) explain that over time societies are likely to adjust their attitude towards water consumption following the construction of new supply infrastructure. Unanticipated spikes in demand can increase vulnerability during drought events, especially if the new supply infrastructure cannot respond flexibly to the change in water use patterns. This vulnerability can be worsened in the period following a drought event due to 'rebounding' water use, when communities may increase their water use during wetter weather (Gonzales & Ajami, 2017). Water system models often omit these key feedbacks between hydrological and social change, thus introducing further uncertainty to the planning problem.

2.2.4 Infrastructure, capacity expansion, and costs

As described in **Section 2.1**, water system models use algebraic equations to represent existing and new water supply infrastructure such as reservoirs, boreholes, river withdrawal points, desalination plants, water treatment works, transfers, and pumped

storage. Information on the features and operation of water supply infrastructure can be sourced from publicly available databases, conversations with environmental regulators, water authorities and other stakeholders, or where possible from field observations. Collaboration with water authorities can facilitate model development and ensure that important features of the system are appropriately represented in simulation experiments, whilst conversations with water managers can inform modelling assumptions that will help to improve simulation efficiency. These assumptions may include aggregation of similar surface water supplies, or the omission of water supply sources with inconsequential yields.

Data availability also influences the modelling assumptions about infrastructure included in the system model. For example, the active capacity of surface water reservoirs can be affected by siltation rates (Jeuland & Whittington, 2014) and evaporation (Herman et al. 2014; Kirsch et al. 2013), yet many water resource assessments do not account for these factors due to lack of data on reservoir levels. Likewise, the 'dead water storage' at the bottom of reservoirs is included in potable water estimates, despite this water being unusable due to its poor quality (Dobson et al. 2020). The travel time of water through the supply network is also difficult to capture in simulation, owing to lack of understanding on flow travel time along river networks and aqueducts. In most network-flow models, flow is assumed to move instantaneously along model arcs. Where possible operational flow rates are assigned to individual arcs within the system model (Chung et al. 2009), although this less common for large, highly interconnected water systems as it increases simulation run-times.

Water planners must also consider the uncertain feedbacks associated with infrastructure capacity expansion, which result from estimations of infrastructure construction delays or overruns (Grimsey & Lewis, 2002), operating and capital

expenditures (Brown & Wilby, 2012), and economic discount rates (Stakhiv, 2011). Operational costs are uncertain as they rely on energy prices and can change with technological developments. Rothausen & Conway (2011) argue for the need to explicitly integrate energy use into water resource management, recognising the full spectrum of energy use within the water sector and how it may change with regulation. The intensity of energy consumption will also vary considerably through time and space, with specific technologies applied in different stages of the water supply network using different amounts of energy for varying durations. Uncertainty surrounding adaptation option selection will increase into the future as technologies improve. Desalination, for example, incurs high capital and operational costs at present, making it a risky solution to many water planning problems. New innovation in desalting technologies, however, is helping to reduce the energy gap between salt water and fresh water desalination, using energy recovery devices to minimise the energy loss in high pressure brine desalination (Plappally & Lienhard V, 2012).

Adaptation options with high energy consumption, like wastewater reuse or desalination, are subject to further uncertainty as they may be inconsistent with wider climate change mitigation narratives (Bates et al. 2008). Uncertainty surrounding energy use, or consequences of use such as carbon cost, should be considered when evaluating the decision space of water planning problems. As identified by Reffold et al. (2008), this can be crucial when choosing adaptation options, as demand management options have low operation emissions, whilst supply-side measures are more likely to result in an increase in GHG emissions. Uncertainty also arises from unforeseen costs associated with switching to alternative infrastructure pathways if hydro-climatic, political or social conditions diverge from the anticipated trajectory. Infrastructure inefficiencies and unused assets are likely to emerge if these uncertainties are not considered (Haasnoot et al. 2019).

Finally, previous work reveals that infrastructure planning is sensitive to the choice of economic discount rate, with potential rates ranging from 3 to 10% (Stakhiv, 2011). Few water planning studies consider uncertainty around economic discount rates, choosing instead to assume that discount rates will remain constant through time.

2.2.5 Policy and regulation

Policy and regulation play a key role in water resources planning, exerting control over water system operation and allocation (Walker et al. 2003). In water planning, objectives set by policy makers and regulators are often designed to improve system performance, reduce environmental impacts, increase regional and national cooperation, and meet global goals.

When defining the planning problem, water planners must consider existing policy and regulatory constraints and judge if (and how) they may evolve with time. This is particularly important when evaluating new adaptation options, which may be sensitive to changes in regulation. For example, water withdrawals (river abstractions) and reservoir operations have to operate in a way that satisfies environmental flow constraints downstream. In the face of increased extreme climatic and hydrologic conditions, and intensified anthropogenic activity, river flow regimes are frequently deviating from regimes observed in historical records (Laize et al. 2014; Schneider et al. 2013). This can impact aquatic food webs (Ledger et al. 2013; Lu et al. 2016; Woodward et al. 2012), ecosystem habitats (Davies et al. 2014; Naiman et al. 2008), and water quality (Watts et al. 2015; Whitehead et al. 2009). In response, regulatory constraints and operating policies should be re-designed to increase water security (Ehsani et al. 2017), protect riverine ecosystems (Yin et al. 2012), and minimise flow alterations from the natural flow regime (Arthington et al. 2006). In addition to the uncertainty surrounding impacts of climate

change to aquatic environments (Wilby et al. 2010), these regulatory changes introduce additional uncertainty to the water planning problem. Future decisions concerning water use regulation by an administrative institution have the potential to influence the success of water supply options being considered at present.

Uncertainty also exists in long-term water system planning for co-riparian nations. Conflict over transboundary rivers, shared surface water sources, and transboundary groundwater conflicts can complicate water planning problems, particularly under scenarios of increased water stress (Bakker & Duncan, 2017; Gorelick & Zheng, 2015). Whilst it is difficult to anticipate how conflict may manifest, it is important for the water planner to consider the socio-political implications of adaptation options and consequences of how they are managed by different communities throughout the river basin. Uncertainty surrounding transboundary negotiations between competing water users has been well demonstrated, with examples for the Murray Darling basin in Australia (Grafton et al. 2011) and the Blue Nile basin in Ethiopia, Sudan and Egypt (Wheeler et al. 2018).

2.3 Decision making under uncertainty

As highlighted in the discussion above, uncertainties exist at multiple levels in water planning problems. This uncertainty is commonly dealt with by (i) varying climate, hydrologic and water system model parameters and forcing data, and (ii) by simulating adaptation options against a range of different scenarios of change. From here on in, the term scenario refers to plausible future states of the world, as characterised by combinations of water supply (e.g. climate change driven flow) and water demand conditions. Traditionally, water planning problems are solved by cost-benefit analysis (CBA) using scenarios of historical observations of demand and flow. Newer CBA frameworks are conducted alongside sensitivity analyses and robustness checks to ensure

that adaptation policies perform in an uncertain future (Ben-Haim, 2006). As previously established, water resource planning and management has moved away from CBA planning frameworks towards methods with improved representation of structural, parametric, and sampling uncertainties (Herman et al. 2020). For example, several methods exist to capture uncertainty in streamflow projections, including: stochastic streamflow generation using historical observations (Borgomeo et al. 2015; Nazemi et al. 2013); stochastic streamflow generation using GCM and RCM projections (Borgomeo et al. 2016), or weather generators (Glenis et al. 2015; Steinschneider & Brown, 2013), and; non-stationary stochastic streamflow generation via direct parameterisation of GCM projections (Borgomeo et al. 2018; Fletcher et al. 2019). When these hydro-climatic flows are combined with scenarios of future water demand, it is possible to evaluate adaptation actions against exponentially large ensembles of future realisations.

This section evaluates the decision support frameworks that have emerged from an improved understanding and representation of uncertainty in water resource planning and management problems. Following the classification outlined by Herman et al. (2020), the discussion is divided into robust and dynamic planning methodologies. Both approaches utilise sets of synthetic scenarios and modelling frameworks to inform decision making, but differ in their representation of uncertainty and solution structure.

2.3.1 Robust planning

Robust planning frameworks use ensembles of future scenarios to robustly identify planning solutions and the conditions under which the system is vulnerable to failure (Weaver et al. 2013). Robust approaches assume that no one realisation of future conditions is more likely than another (Knight, 1921), and so seek to find solutions that perform satisfactorily, or satisfice minimum performance criteria, over a wide range of

plausible scenarios (Matrosov et al. 2013). Several schools of thought have emerged from the robust planning rhetoric, including Robust Decision Making (Groves & Lempert, 2007; Lempert & Collins, 2007), Many-Objective Robust Decision Making (Herman et al. 2014), Info-Gap Decision Theory (Ben-Haim, 2006; Korteling et al. 2013), Risk-Based Decision Making (Borgomeo et al. 2018, 2016), and Decision Scaling (Brown et al. 2012; Brown et al. 2011; Poff et al. 2016; Taner et al. 2019).

Robust Decision Making (RDM) uses 'scenario discovery' to develop robust plans (Bryant & Lempert, 2010; Groves & Lempert, 2007). Kwakkel et al. (2016) split RDM into four steps: (i) participatory scoping – to define the system, identify key uncertainties, identify candidate strategies comprised of policy and adaptation options, and study outcomes; (ii) case generation – to estimate strategy performance against future scenarios; (iii) scenario discovery – to characterise strategy vulnerability to the key uncertainties identified in step one, and; (iv) trade-off analysis – to evaluate strategy performance across the different outcome indicators and identify robust strategies. Despite appearances, the steps in RDM are not linear, with information generated by individual steps continuously providing new insights on system vulnerabilities and strategy robustness. Within the literature, RDM has been used widely to identify robust adaptation options under climate change. For example, Jeuland & Whittington (2014) use principles of RDM to identify real options and reservoir operating rules for the Blue Nile in Ethiopia. Groves et al. (2015) use RDM as a quantitative decision support tool to evaluate scenarios of demand, climate conditions, local resource availability, and management challenges in the Metropolitan Water District of Southern California. Through scenario discovery, Groves et al. (2015) identify future conditions under which a principle water allocation strategy fails, providing Metropolitan water agencies with the information needed to guide adaptive management

in the face of future uncertainties. Using RDM, the water planners are also able to avoid system failure during vulnerable periods.

Many-Objective Robust Decision Making (MORDM) is an extension of RDM, using many objective optimization to inform planning in complex environmental systems (Kasprzyk et al. 2013). The framework utilises multi-objective evolutionary algorithms (MOEAs) to search for and identify trade-offs in conflicting performance measures inherent to the water planning problem. These measures include adaptation costs, system reliability and efficiency, and environmental costs (or benefits). The search for planning solutions using MOEA precludes the robust decision-making stage, which is used to evaluate the robustness of candidate solutions to uncertain future conditions. As Herman et al. (2014) demonstrate, the MORDM framework finds and communicates key stakeholder dependencies in water resource planning, trading-off robustness and system performance under deeply uncertain future conditions.

Risk-based decision analysis is similar in conception to MORDM, using risk as a performance indicator of water system performance in many objective searches under uncertain future conditions. In risk-based decision making, planning solutions are measured in terms of risk reduction achieved by adaptation intervention (Garrick & Hall, 2014). In this thesis, risk is defined as the probability and consequences of an event occurring. In water planning, risk typically arises from flooding events, droughts, water shortages, pollution incidents, or ecosystem damage. Risk-based approaches commonly trade-off risk with adaptation cost, identifying the best combination of planning interventions that perform acceptably against large ensembles of climate and demand scenarios (Borgomeo et al. 2016). Recent work has expanded risk-based decision approaches to incorporate elements of RDM. For example, Borgomeo et al. (2018) use multi-objective optimization to identify planning portfolios for the London water system

that trade-off robustness with adaptation costs for set levels of risk. Using frequency and severity of water shortages as an indicator of risk, the study shows how robustness and risk against uncertain future conditions can be improved incrementally with increasing levels of adaptation. Much like MORDM, the multi-objective evolutionary algorithm used in the search for adaptation portfolios trades-off objectives fundamental to the planning problem.

Whilst RDM evaluates competing planning alternatives against the entire uncertainty space, Info-Gap Decision Theory (IGDT) uses nested sets of plausible future conditions to evaluate the performance of individual planning portfolios (Ben-Haim, 2006). This 'local analysis' starts from the 'best estimate' of future uncertainty (Herman et al. 2014), gradually exposing the system to more uncertain conditions. Using IGDT, a planner is able to identify the range of uncertainty that a planning alterative can perform reasonably under (Woodward et al. 2014). IGDT helps to eliminate strategies with limited robustness, with stakeholders able to specify minimum levels of performance required for their system. Despite their similarity (Hall et al. 2012), RDM and IGDT can be used together to provide decision makers with complementary information on the robustness of water supply portfolios to future uncertainties (Matrosov, et al. 2013).

Finally, Decision Scaling offers a robust bottom-up risk assessment of threats to water supply systems (Brown et al. 2012). Similar to IGDT, decision scaling requires stakeholders to define indicators and condition-specific thresholds required to maintain acceptable system performance. Informed by stakeholder discussions, a stochastic analysis identifies system sensitivity to key drivers of change (e.g. climate states, demographic growth). Using this analysis and stakeholder defined thresholds, risk (i.e. the likelihood of exceeding condition-specific thresholds) is estimated using projections of future change. Decision scaling has been applied to both climate risk assessments in the water sector

(Brown et al. 2012) and sustainable freshwater management (Poff et al. 2016). Much like MORDM and risk-based planning, decision scaling allows better representation of important, but often conflicting, performance criteria inherent to water management problems. This is particularly important for complex water systems with competing stakeholder interests, where important trade-offs may emerge when the system is exposed to uncertain conditions that are not represented in historical records (Barbour et al. 2016).

2.3.2 Dynamic planning

Dynamic planning deals with uncertainty by generating adaptation policies that evolve as conditions are realised over time. Unlike robust planning, dynamic planning methods do not specify the timing of adaptation actions decades into the future, instead developing optimal plans that respond to indicators of system change. Dynamic planning can be treated as an optimal control problem (Herman et al. 2020), seeking to minimise the impact of uncertainty on policy outcomes in a dynamically changing system. Multiple approaches illustrate how new information can be used to make decisions about infrastructure, operations and policy. The principle frameworks include Dynamic Adaptive Policy Pathways (Haasnoot et al. 2013; Kwakkel et al. 2015), Dynamic Adaptive Planning (Kingsborough et al. 2016), Stochastic Dynamic Programming (Fletcher et al. 2019; Luo et al. 2007), and Real Options Analysis (Cardin & Caunhye, 2017; Erfani et al. 2018; Jeuland & Whittington, 2014; Wang & De Neufville, 2005).

The Dynamic Adaptive Policy Pathways (DAPP) approach was designed to avoid making inappropriate and unnecessary adaptation decisions under uncertain climate, technological, socio-economic and political states (Haasnoot et al. 2013). Combining principles of ‘Adaptive Policymaking’ (Kwakkel et al. 2010) and ‘Adaptive Planning’ (Haasnoot et al. 2012), DAPP generates a sequence of possible actions that are triggered

if and when the action is needed in the future. A combination of signposts and tipping points are used to monitor conditions in real time, allowing immediate adaptation response as new information appears. Case study applications of the framework to the Ijsselmeer (Haasnoot et al. 2013) and Waas (Kwakkel et al. 2016) areas in the Lower Rhine Delta demonstrate the importance of dynamic adaptation when multiple decision pathways (or adaptation solutions) exist. Taking inspiration from the DAPP framework, Zeff et al. (2016) develop an adaptive approach to inform inter-utility water transfers in the 'Research Triangle' area of North Carolina. Using continually updated risk-of-failure metrics, the decision-making framework considers both short-term operating agreements (transfer capacities) and long-term investment decisions (infrastructure development). The framework successfully responds to changing reservoir storage and water demand patterns with conservation measures and regional water transfers, enabling better coordination of shared resources between multiple stakeholders.

The rationale to incorporate adaptation pathways into water systems planning is further reinforced by Kingsborough et al. (2016), who develop an integrated dynamic adaptive planning and risk assessment framework to support long-term planning of the London water system. Building on DAPP, the method identifies adaptation pathways consisting of supply and demand side options that mitigate against the risk of water shortages in the London water supply system. The pathways are tested against transient climate change driven future flows, and the probability of exceeding a target frequency of water use restrictions is recorded for individual simulations. Results indicate that dynamic adaptation pathways offer different degrees of flexibility, allowing decision makers to choose pathways that best represent their attitudes toward risk and residual uncertainty. Consistent with DAPP, Kingsborough et al. (2016) stress the importance of pathway reappraisal as new climate and socio-economic-political information becomes available.

As discussed throughout this chapter, this is especially important in systems vulnerable to uncertain drivers of change.

Stochastic Dynamic Programming (SDP) offers an alternative approach to adaptive planning, developing optimal flexible planning strategies through incremental learning and updated uncertainty estimates of climate states. Dynamic programming is the theory of multistage decision processes (Bellman, 1957), taking an optimization problem and dividing it to create a set of smaller problems. The smaller problems are represented as a network of nodes and links, and must be solved before the optimal solution can be identified. Fletcher et al. (2019) use SDP to incorporate learning about climate change uncertainty in dynamic water infrastructure planning. Using GCM projections, the proposed methodology generates ensembles of future climate conditions, from which climate uncertainty for individual observations can be estimated using a Bayesian statistical model. The uncertainty estimates represent new information learned at different stages in the planning horizon, and are used within a stochastic dynamic program to generate adaptive planning policies that respond flexibly to 'new information'. The case study example compares the performance of flexible and robust approaches for dealing with climate change uncertainty, quantifying the value added by incorporating learning into water planning problems. Results indicate that flexibility is especially important for water planners considering large, irreversible infrastructure investments.

Real Options Analysis (ROA), or engineering analysis, is "an approach to decision making that formally recognises uncertainty and examines how current decisions limit or expand our ability to learn and react in the future" (Baker et al. 2012, p. 1). Consistent with the methods presented so far, ROA helps avoid making unnecessary, ill-informed decisions based on uncertain forecasts. Specifically, ROA offers opportunities to delay investment, abandon or switch adaptation pathways, and expand the capacity of adaptation

options. Wang & De Neufville (2005) describe two types of real options: real options 'on' systems use financial valuation methods to hedge against risk, whilst real options 'in' systems introduce flexibility to the structural design of infrastructure. Real options 'in' systems are more common in water resource planning, because water planners are able to alter the design of the current system in order to exploit opportunities made available as uncertainty is learned through time (Steinschneider & Brown, 2012). Examples of 'in' systems include purchasing land ahead of scheduled construction works, investing in pumps to draw up dead storage, and installing pipelines to connect storage reservoirs. Woodward et al. (2014) and Erfani et al. (2018) illustrate the value of real options analysis in adaptive water planning. Using a flood risk analysis tool and a multi-objective genetic algorithm, Woodward et al. (2014) identify optimal adaptive strategies to reduce coastal flood risk in the Thames Estuary by 2100. Normal distributions are constructed using the 5th, 50th and 95th percentiles of sea level rise under different UKCP09 emissions scenarios, and specific future realisations of each distribution represent uncertainty in future climate at each time-step in the planning horizon. Much like DAPP, if a given realisation projects sea level rise above a specific threshold an adaptation option is triggered. If the threshold is not reached the plan follows a lower path in a coded decision tree. Results reveal that adaptable strategies with real options have pareto-dominance over deterministic strategies, as the real option schemes reduce the likelihood of large-scale infrastructure expansion and remove the need for large initial costs. This conclusion is echoed by Erfani et al. (2018), who quantify the improvement in net present value (NPV) cost achieved using Real Options Analysis to identify adaptive and flexible plans for the London water supply system. Across a 50-year planning horizon, adaptive solutions could avoid £100 million NPV through delayed option scheduling or replaced investment interventions.

2.4 Critique and moving forward

The decision-making frameworks described in this chapter illustrate the breadth and depth of research dedicated to dealing with uncertainty in water resources planning. Each approach provides a platform to manage one or more sources of uncertainty, evaluating adaptation actions against multiple planning objectives and plausible future states of the world. However, the existing planning methods are not beyond improvement. This thesis targets three principle limitations that exist in current decision-making literature.

2.4.1 Limitation 1

A commonly cited limitation of robust planning frameworks is the inability to dynamically represent decision making in the face of changing conditions. Robust planning techniques typically generate static plans that perform well against the envelope of scenarios they're evaluated against. Yet if critical uncertainties are not well represented by the scenario ensembles and water system model, the optimal plan may over perform and incur excessive upfront costs, or underperform and cause disruptions to water consumers (Borgomeo et al. 2018; Wilby & Dessai, 2010). The vulnerability of static plans to unforeseen future conditions can be classified as false-positive adaptation (over adaptation) and false-negative adaptation (under adaptation) (Beven, 2016; Robinson & Herman, 2019). As discussed previously, dynamic planning frameworks avoid issues of false-positive and false-negative adaptation through the use of indicators (signposts) and triggers to initiate adaptation under non-stationary conditions. However, dynamic plans cannot be considered robust to future uncertainties if (i) adaptation signposts inadequately represent uncertainties inherent to the water system being modelled, and (ii) decision triggers are over-fit to the scenarios of uncertainty used in the plan generation process. To test for over-fitting, dynamic plans can be simulated against a wider range of uncertainties

after the initial strategy generation phase. For example, Fletcher et al. (2019) revaluate optimal flexible water infrastructure strategies generated by SDP against scenarios not used in the initial strategy generation phase.

Of the select planning frameworks that integrate dynamic and robust planning methodologies, few offer a clear process for indicator selection, threshold definition, infrastructure option evaluation, *and* multi-objective optimization of adaptation actions against an ensemble of future scenarios. Moreover, the planning approaches that do use indicators of change to inform adaptation decisions are commonly limited by the 'informativeness' of selected indicators and their relevance to performance metrics of the modelled system (Raso et al. 2019). Significant scope exists to improve indicator-based water planning frameworks, by using data-driven techniques common to robust planning methods to identify informative indicators and trigger thresholds unique to dynamic plans. In response to the limitations highlighted here, **Chapter 4** presents a dynamic risk-based water planning framework that is informed by an extensive ensemble of hydro-climatic flow and demand scenarios. The chapter outlines the steps needed to rigorously identify indicators of change to be monitored in simulations of the water system and used to trigger adaptation actions. The indicators and thresholds inform rule-based adaptation strategies and are optimized against fully risk-based performance metrics. Unlike previous studies, the multi-dimensional metrics used in **Chapter 4** are explicitly risk-based as they consider duration, severity, *and* frequency of observable water shortages.

2.4.2 Limitation 2

Within the decision making literature, it is common for water planning frameworks to target uncertainties intrinsic to single water supply systems (e.g. Erfani et al. 2018; Kingsborough et al. 2016; Matrosov et al. 2015). However, research has shown that 21st

Century climatological and hydrological drought events may impact water availability across different spatial scales, and will likely to affect patterns of water security in highly connected regions (Dobson et al. 2020). This is problematic for neighbouring water systems that rely on shared resources, and for systems that depend on a reliable supply of water from a geographically distinct location (Palmer & Characklis, 2009; Zeff et al. 2016, 2014). Heterogeneity in patterns of water use and competing stakeholder attitudes of risk add additional complexity to the operation and adaptation of integrated water supply systems.

Despite this, little has been done to explore the reliability of inter-basin water supply infrastructure against spatially heterogeneous uncertainty. **Chapter 5** addresses this information gap. In line with the robust planning rhetoric, the chapter explores the resilience of adaptation infrastructure to spatially extensive and severe drought events. The proposed framework builds on existing water planning methods to evaluate the level of risk (Borgomeo et al. 2018) and reliability (Paton et al. 2013) of transfer infrastructure during drought events not present in the historical record. By focussing on droughts, the research specifically targets uncertainty in climate impacts that have previously been difficult to quantify (Herman et al. 2020). Unlike previous transfer-centric studies, the results also highlight the importance of simulating the joint occurrence of co-dependent droughts in shared water resource systems, and the consequences of evolving drought dynamics on infrastructure operation, cooperation, and reliability.

2.4.3 Limitation 3

The planning approaches discussed in this chapter primarily examine uncertainties arising from changes in climate, hydrology, demography, and water demand. In these approaches, it is rare to formally use aquatic health as a performance metric in risk- or robustness-

analyses. Environmental impacts are commonly dealt with implicitly through crude hydrological measures (Acreman et al. 2014), are monetised (Matrosov et al. 2013; Padula et al. 2013), or are considered after planning solutions have been generated (Borgomeo et al. 2016). With the exception of Poff et al. (2016), few studies consider the feedbacks and trade-offs between adaptation, water system regulation, and uncertainties in ecosystem response. Similar criticism applies to the freshwater science and environmental flow literature, with an abundance of studies examining the influence of flow regime on river ecosystems (Acreman et al. 2014; Bunn & Arthington, 2002; Monk et al. 2006), but few investigating the interaction between management decisions and aquatic health.

In the face of climate and socio-demographic uncertainty, it is essential to consolidate environmental science and water planning when designing adaptation management portfolios (Poff, 2018). Planning approaches should reflect the dynamism of ecosystems under shifting hydro-climatic regimes (Arthington et al. 2018), whilst accounting for emerging uncertainties in policy and regulation. The research presented in **Chapter 6** addresses these limitations, exploring how the impact of adaptation actions on aquatic health can be quantified using historical data and future scenarios of change. Using simulation techniques, the research investigates the success of regulation policies under climate and demand uncertainties. The results highlight important emerging trade-offs between water supply security and environmental degradation, further emphasising the need to better represent aquatic health in 21st Century water planning problems.

2.4.4 Summary of proposed research

i. **Addressing limitation 1:** Develop a rule-based decision-making framework that builds on data-driven techniques common to risk-based planning methods to identify indicators and thresholds that inform adaptation actions;

ii. **Addressing limitation 2:** Examine the performance of inter-basin infrastructure to spatially heterogeneous climate and demand uncertainties;

iii. **Addressing limitation 3:** Promote greater representation of aquatic health and regulatory uncertainties alongside climate change and demand uncertainties in water planning problems.

3 Data and models

Water systems analysis requires climate and flow scenarios, water demand projections, information on system operation, regulatory constraints, and characteristics of key decision variables (i.e. type of adaptation option). This chapter reviews the data and modelling tools used in **Chapters 4**, **5**, and **6**. The chapter is structured following the modelling framework illustrated in **Figure 3.1**.

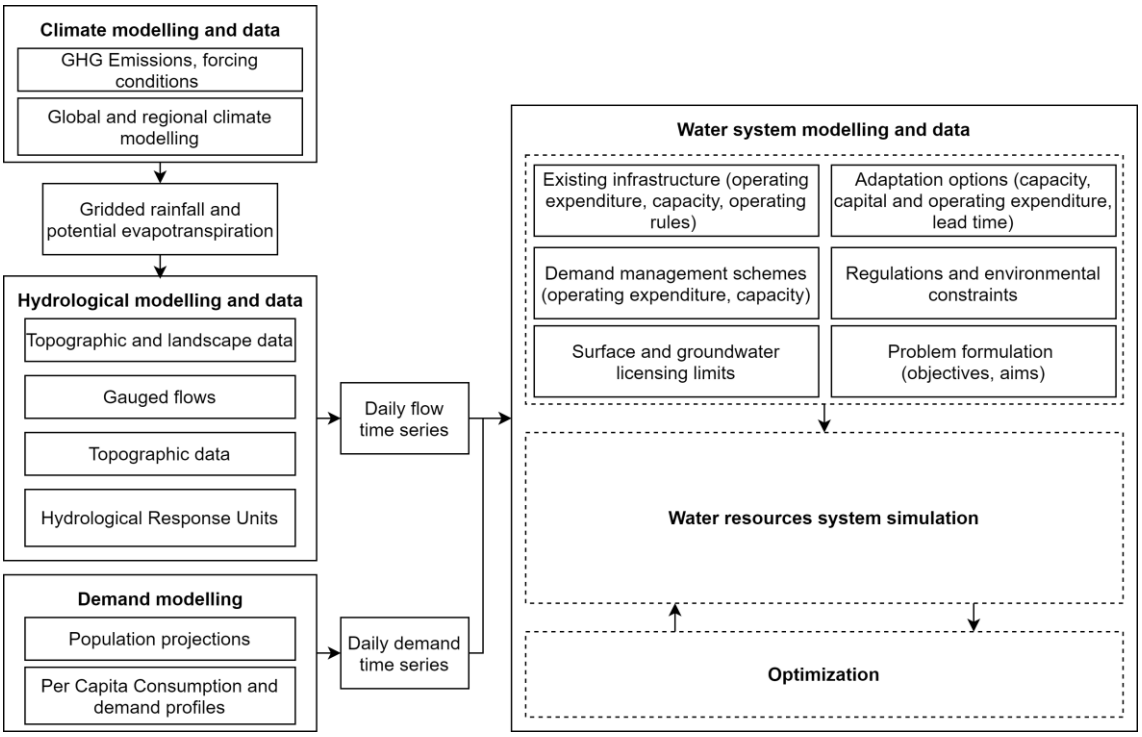


Figure 3.1. Modelling framework for thesis research chapters.

3.1 Climate modelling

As established in **Chapter 2**, emission driven climate change projections are frequently used in climate impact assessments and decision-making frameworks. Climate projections are ideal for water systems analysis, extending beyond the range of current climatological

variability and providing the basis for testing the robustness of water resources management plans to future climate related uncertainties. Furthermore, incorporation of climate model outputs into water systems planning allows water managers to estimate the impact of climate change on important decision variables in the water system. Quantifying climate related risks in this way improves communication to key stakeholders not familiar with principles of climate science.

The methods presented in this thesis rely on large ensembles of high-resolution climate change driven weather sequences. Previously, UK-based impact assessment studies typically used large climate 'super-ensembles' derived from UKCP09 climate projections to drive rainfall runoff models (e.g. Borgomeo et al. 2014; Borgomeo et al. 2016; Erfani et al. 2018; Huskova et al. 2016). Using information from the Intergovernmental Panel on Climate Change, a selection of emissions scenarios and a large perturbed physics ensemble of HadCM3 GCM (Murphy et al. 2009), UKCP09 projections offer probability distributions of change factors in temperature, precipitation and evapotranspiration relative to the baseline climatology. As illustrated by Borgomeo et al. (2014), a stochastic weather generator can be used alongside UKCP09 change factors to generate large ensembles of weather variables for future time periods.

As discussed, the range of uncertainty in modelling frameworks increases as the number of methodological steps increases (Wilby & Dessai, 2010). Therefore, inclusion of a weather generator to generate weather sequences using UKCP09 projections introduces an additional level of parametric and structural uncertainty to decision making frameworks. For this reason, the research presented in this thesis takes advantage of state of the art climate output from Weather@Home (Climateprediction.net, 2015; Guillod et al. 2017, 2018), a climate modelling platform that uses computing power of volunteers to generate large ensembles of high-resolution climate sequences. Weather@Home uses

output from global climate model (HadAM3P) with nested regional climate model (HadRM3P) and land surface processing (Guillod et al. 2017) to produce weather sequences for Baseline (1975-2004), and Near Future (2020-2049) and Far Future (2070-2099) time periods under RCP 8.5. In addition to reducing the number of steps required to generate weather sequences, Weather@Home is considered advantageous over methodologies using weather generators as it is able to reproduce climatology across multiple study areas. Because Weather@Home is process based, it is able to pick up physical forcing processes that better represent the relationship between precipitation and potential evapotranspiration through space. The Weather@Home weather sequences are more spatially consistent than those produced by grouped weather generators, and can better produce spatially coherent droughts that can be used to stress test interconnected infrastructure systems. This is particularly important for water planning assessments that examine water resource availability across basins, catchments, and water companies.

The Weather@Home weather sequences have been used to study the impact of climate change on water resources planning problems in the Thames Basin (Borgomeo et al. 2018), sea surface temperature driven extreme weather events in England (Haustein et al. 2016), heat related mortality in London and Paris (Mitchell et al. 2016), and flood damage in Southern England (Schaller et al. 2016). Across Europe, Weather@Home weather sequences are available at 25km^2 resolution for the Baseline, Near Future, and Far Future time periods. Individual scenarios are generated using the same climate model, and can therefore be treated as equiprobable (i.e. one scenario is no more likely than another). In the Thames Basin, Baseline scenarios of precipitation and temperature have been shown to reproduce historical observations well, with the range of historically observed drought events represented across the 100 member Baseline ensemble (Borgomeo et al. 2018). The Near and Far Future ensembles contain drought events not present in historical records,

therefore providing a wider range of conditions to examine adaptation options against. This is particularly useful for robustness assessments that identify climatic conditions under which the system will fail.

3.2 Hydrological modelling

3.2.1 Surface water modelling

Water resource models require input from surface and groundwater sources. Rainfall-runoff modelling is necessary to transform the ensembles of Weather@Home weather sequences discussed above into flows that can be fed into a water resources model. Innumerable rainfall-runoff modelling frameworks exist to do this, including CATCHMOD (Wilby et al. 1994), TOPMODEL (Beven et al. 1984), INCA (Whitehead et al. 1998), and DECIPHeR (Coxon et al. 2019). In the event that a rainfall-runoff model is unavailable to a water resource modelling, the Future Flows Hydrology and Groundwater Dataset by Prudhomme et al. (2013) could be used as input for the water resources model. The Future Flows dataset offers an 11-member ensemble of daily river flow and groundwater levels from 1951-2098 when simulated under the Future Flows Climate Data (Prudhomme et al. 2012).

In this thesis, the Dynamic fluxEs and ConnectIvity for Predictions of HydRology (DECIPHeR) modelling framework by Coxon et al. (2019) was selected over other rainfall-runoff models because it is a quick and powerful way to perform rainfall-runoff modelling across multiple catchments with different hydrological characteristics. DECIPHeR was chosen over the Future Flows dataset because it offers a larger ensemble of climate change driven flows against which adaptation options and policies can be simulated against.

DECIPHeR has been shown to reproduce daily observed flow well across a range of catchments in England and Wales (**Figure 3.2**). To evaluate model performance, Coxon et al. (2019) ran DECIPHeR with 10,000 parameter sets randomly sampled from a uniform distribution. Historic flows (1961-2015) were simulated using precipitation (P) and potential evapotranspiration (PET) from the CEH datasets: GEAR (Tanguy et al. 2019) and CHESS-PE (Robinson et al. 2016), respectively. The 10,000 parameter sets simulate daily flows for 1,366 gauging station locations across the UK and were evaluated against historically observed flows from the National River Flow Archive (NRFA; NERC CEH Wallingford, 2018) that were naturalised using the Environment Agency's National Abstraction Licence Database (Environment Agency, 2013b). Hydrological signatures, model performance metrics (Nash-Sutcliffe efficiency, slope of flow duration curve, bias in runoff ratio and low flow volume), and time series statistics were used to inform model evaluation and identify the top 1% of model simulations. Whilst the parameter sets evaluated do not investigate the entire parameter space, the final behavioural ensemble of parameter sets reproduce flow statistics well, with 98% of gauged flows meeting the low flow performance threshold. Slope of the flow duration also performs well (96% of flows), whilst bias in runoff ratio proves more difficult to reproduce (75% of flows) (Coxon et al. 2019). Discrepancy in runoff ratios is most noticeable in simulated flows in the South East, attributable to greater human activity in densely populated areas and larger abstractions from surface and groundwater sources. Whilst this may be considered problematic for the regions of interest in this thesis, DECIPHeR's model ability to capture the range of hydrological historical behaviour is satisfactory when valued against Nash-Sutcliffe Efficiency and log Nash-Sutcliffe Efficiency (see Appendices in **Chapters 4**, **5**, and **6**).

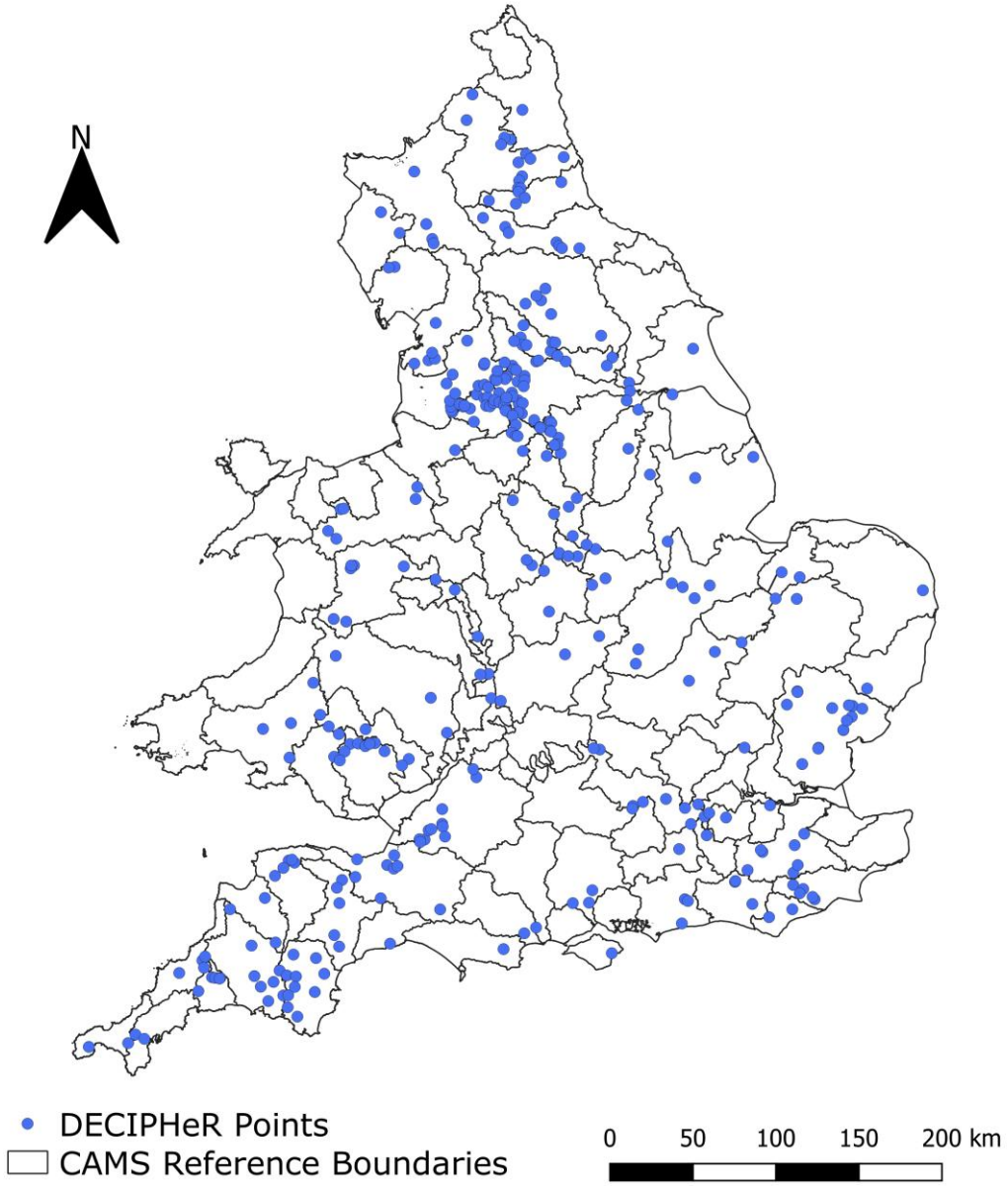


Figure 3.2. GIS depiction of DECIPHeR (Coxon et al. 2019) inflow points for catchments in England and Wales. Catchment boundaries are defined according to the Environment Agency Catchment Abstraction Management Strategy (CAMS) reference boundaries (Environment Agency, 2013a).

Future flows are simulated using projections of precipitation and potential evapotranspiration from Weather@Home for the Baseline (1975-2004), Near Future (2020-2049) and Far Future (2070-2099) periods (**Figure 3.3**). Weather@Home time

series of P and PET are downscaled from 25km resolution to a 5km grid, following the downscaling method by (Guillod et al. 2018). The best performing parameter set is used to simulate flows using each W@H weather sequence, creating 100 projections for multiple input points in England and Wales. The research presented in this thesis uses the simulated flows for catchments in the Thames and Severn Basins.

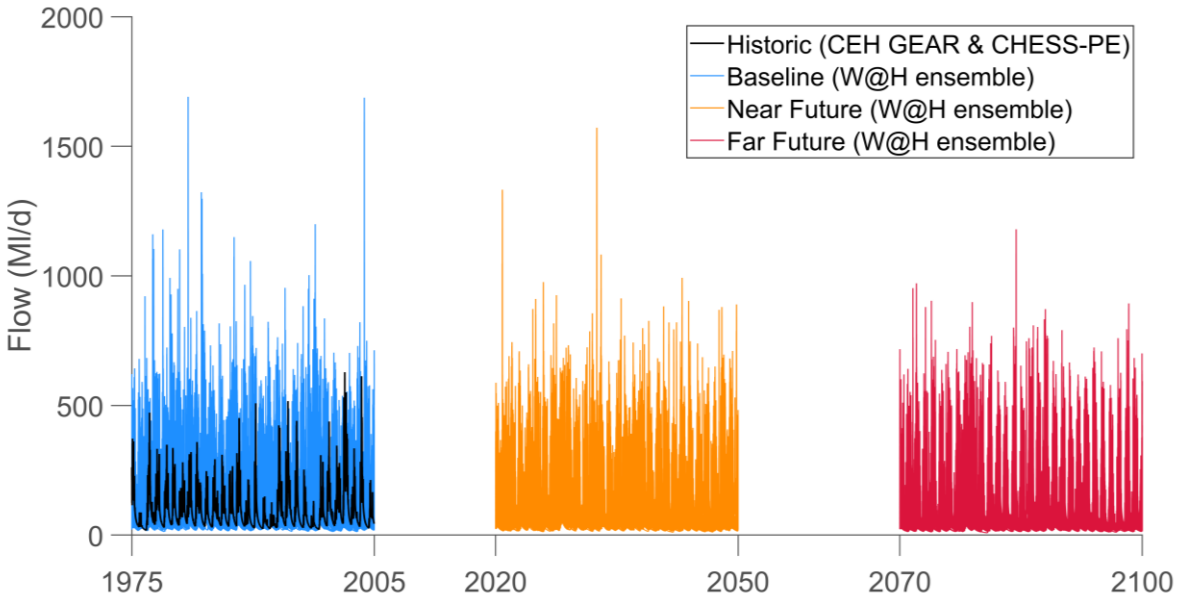


Figure 3.3. Naturalised flows at Teddington Weir (National River Flow Archive – gauging station 39001) simulated using DECIPHeR modelling framework. Flows are simulated for Historic period (1975-2004, black line) using CEH GEAR (Tanguy et al. 2019) and CHESS-PE (Robinson et al. 2016) datasets, and Baseline (1975-2004, blue lines), Near Future (2020-2049, orange lines), Far Future (2070-2099, red lines) ensembles using Weather@Home weather variables (Guillod et al. 2017).

3.2.2 Groundwater modelling

Changes in groundwater availability under climate change are not considered in this thesis. Due to the complexity of determining water availability in individual water supply

boreholes, output from groundwater sources is taken as constant throughout water system simulations and is set at the licence abstraction limit, defined by the Environment Agency (Environment Agency, 2013b). Admittedly, this presents a significant limitation of the decision-making frameworks presented in subsequent chapters. However, after careful consideration groundwater forecasting was determined to be beyond the scope of the thesis aims and objectives. As Gorelick & Zheng (2015) argue, one of the greatest challenges to groundwater management is translating modelling uncertainties into decision support systems with metrics of tolerable risk. Whilst not addressing this issue explicitly, this thesis advocates for improved understanding of the role of groundwater depletion in water supply system failure, and for better representation of groundwater uncertainty in water system modelling.

3.2.3 Water quality modelling

Whilst water quality plays an important role in infrastructure planning, it is not considered as a constraint in the modelling frameworks presented in this thesis. In simulations, water quality is assumed constant on the condition that regulatory requirements (minimum required flow, abstraction licences) are satisfied. Undeniably, this is a considerable methodological limitation. However, the principal themes explored in **Chapters 4**, **5**, and **6** could be used alongside integrated water resources assessments that consider water quality issues. The integrated framework presented by Mortazavi-Naeini et al. (2016) gives a good example of how water quality issues can be considered in risk-based water resource modelling.

3.3 Demand modelling

Public water demand in England makes up 58% of abstracted surface water (Environment Agency, 2013b). In England, water demand is determined for individual geographic regions, termed Water Resource Zones (WRZ). WRZs are highly connected water zones that predominately supply water from sources contained within the WRZ administrative boundaries. In this thesis, demand time series are estimated for WRZs in Thames Water and Severn Trent (**Chapter 5** only).

As established in **Chapter 2**, water demand is a function of population, per capita demand and commercial and industrial demand (Beh et al. 2014). Studies modelling water resources in the Thames Basin typically use (i) water demand projections generated through stochastic water demand forecasting (Matrosov et al. 2013) or (ii) domestic water demand forecasts provided by the water utility (Borgomeo et al. 2018; Erfani et al. 2018; Matrosov et al. 2015). The demand projections used throughout this thesis were created using demographic data, water resource planning tables and demand profiles of per capita consumption. As a result, the number and range of demand projections examined here encapsulate intra- and inter-annual demand-side uncertainty, improving on approaches using scenarios that assume linear annual growth.

80-year demand projections are generated for the decision-making framework presented in **Chapter 4**. Longer projections are required because the proposed framework relies on long-term records of demand and flow. The 100 projections are created from baseline forecasts of water demand (mega-litres, Ml/d) from Thames Water's WRMP19 (Thames Water, 2019a), and are scaled using data on per capita consumption projections (Environment Agency, 2019b) and population projections from the Office for National Statistics (Office for National Statistics, 2016). In **Chapters 5** and **6** shorter (25-30 year) demand time series are estimated from the dry year annual average distribution input at

water resource zone level and scaled according to company water resource planning tables and demand profiles (Severn Trent Water, 2019; Thames Water, 2019a). In line with Borgomeo et al. (2016), all demand projections are considered independent of climatic conditions. This is a recognised limitation of the proposed methodologies, and future work should consider emerging feedbacks between water consumption patterns and a warming climate.

Non-public water (NPW) demands are estimated from observed monthly abstracted volumes between 1999-2015 from the National Abstractions Licence Database (Environment Agency, 2013b). NPW demand is assumed to be constant and aggregated to the catchment scale. Consistent with other water planning frameworks applied to the Thames Basin (Borgomeo et al. 2018; Borgomeo et al. 2016; Matrosov et al. 2013), shortages in non-public water demands are explicitly ignored in the research outcomes.

3.4 Water resource system modelling

3.4.1 System representation and simulation

Water resource modelling and simulation is the best approach available to address water resource problems and to optimize planning solutions. Water system models are tools that can be used to analyse risk and resilience of water systems and to identify infrastructure options that are robust to plausible future conditions of the world (Hall et al. 2019). System models are ideal for decision making frameworks as they are able to replicate the behaviour of water resource systems for a given set of input conditions, such as demand, stream flow, or reservoir flow. Several water systems models exist to support water resource planning, including Water Evaluation and Planning (WEAP; Yates et al. 2005), WATHNET-5 (Kuczera, 1992), RiverWare (Zagona et al. 2001), ResSim (Klipsch & Hurst, 2003), and Interactive River-Aquifer Simulation (IRAS; Matrosov et al. 2011).

The research presented in this thesis uses the generalised node-arc simulation model, WATHNET-5, to represent water supply system in the Thames Basin. WATHNET-5 was chosen for multiple reasons, including: (i) a user-friendly interface; (ii) intuitive pseudo scripting language; (iii) efficient computing time; (iv) integrated multi-objective optimization module, and; (v) capability to run on parallel nodes. WATHNET-5 has been successfully used to estimate the frequency, duration and severity of water shortages in South East England under changing future conditions (Hall et al. 2019), examine scheduling capacity expansion for the bulk water supply system in Canberra (Mortazavi-Naeini et al. 2014), quantify risk and robustness based performance metrics for planning portfolios in the London water supply system (Borgomeo et al. 2018), and optimize water supply headworks operating rules in Sydney (Cui & Kuczera, 2005).

WATHNET-5 represents a water resource system as a network of nodes and arcs, formulating and solving a network flow programme (NFP). The model has six node types (reservoir, demand, inflow, junction, waste and harvest) and two arc types (conduit/pipes and stream). The WATHNET-5 models used in this thesis represent all major supply infrastructure in the Thames Water system, including the London and Upper Thames Reservoirs, boreholes, water treatment and reuse works, river abstraction points, WRZ demand centres, and desalination plants. In simulation, water moves through the network from node to node along connecting arcs. At each time-step in the simulation, WATHNET-5 allocates water to individual nodes by solving a mass balance optimization problem, subject to system constraints and specific mass balance constraints. As with most water system models, the constraints specified for this research comprise of minimum required flows (MRF), pipe and transfer capacities, and abstraction licence conditions. The scripting feature in WATHNET-5 also allows custom rules to be written for individual arcs and nodes, which is especially useful for systems with complex operating procedures.

3.4.2 Water system data

Water resource system models are hard to calibrate and validate, relying on matching simulated reservoir levels to historic records and consultation with professionals in the water industry. Development of the water system models used in this thesis were largely informed by employees of WATER UK[1] and Thames Water Utilities Ltd[2], who gave valuable advice in the model development and appraisal stage to ensure that the models represented features of the Thames Water system well. Data on infrastructure, demand management, operating costs and policies, adaptation options, reservoir release curves, and abstraction licensing was sourced (i) directly from WATER UK, Thames Water Utilities Ltd and the Environment Agency[3], and (ii) by reviewing the 2014 and 2019 Water Resource Management Plans (WRMP). WRMPs are published by UK water companies every 5 years and contain summaries of the water utility's business plan, baseline supply-demand balance, feasible options for future investment, and analysis of climate change risks. The plans provide an overview of key uncertainties in the supply system and the problems targeted in the planning process. Thames Water WRMPs provided a starting point for the research presented in this thesis. However, a comprehensive understanding of system vulnerabilities was established only after conversations with individuals at Thames Water and the Environment Agency. These discussions played an important role in both model and methodological development, providing valuable and critical feedback on modelling experiments and results.

Technological developments (Plappally & Lienhard V, 2012), discount rates (Stakhiv, 2011), and variable energy use (Rothausen & Conway, 2011) introduce significant uncertainty to water planning problems. Whilst this thesis does not explicitly

[1] www.water.org.uk
[2] https://www.thameswater.co.uk/
[3] https://www.gov.uk/government/organisations/environment-agency

tackle these sources of endogenous uncertainty, the proposed decision-making frameworks are designed in a way that allows for these uncertainties to be explored in the future. For example, the vulnerability of adaptation option selection to discount rate uncertainty could be explored using the methodology outlined in **Chapter 4**, through repeated multi-objective optimizations using different discount rates. Planning solutions generated under individual model configurations could then be compared to identify options that are robust to changes in discount rate. In a similar vein, the sensitivity of Pareto-approximate planning solutions could be tested against energy use efficiency estimations to see if the popularity of energy intensive technologies changes as technologies improve.

3.4.3 Multi-objective optimization

WATHNET-5 can be used to conduct multi-objective optimization. Optimization models have been used widely in engineering and infrastructure planning to evaluate adaptation costs and identify optimum solutions to basic planning problems. In water resources planning, multi-objective optimization as a decision making tool is paramount to satisfying the objectives and risk tolerances of multiple users within headworks systems (Cui & Kuczera, 2005). This is also true for multi-reservoir system operation, which must perform to ecological streamflow targets (Steinschneider et al. 2013) and balance upstream and downstream flow during extreme flow periods (Kim et al. 2006).

Multi-objective optimization is a method of evaluating feasible solutions to a water supply-demand problem, which considers two or more objectives simultaneously, and can be defined as “a vector of objective functions and a feasible region defined by a set of constraints” (Liang et al. p. 333). Deb (2001) identifies two objectives of multi-objective optimization: (i) to find a set of feasible solutions as close as possible to the Pareto-optimal

front, and (ii) to find a set of feasible solutions as diverse as possible in the decision variable space. Inspired by principles of natural selection and evolution, multi-objective optimization evolutionary algorithms (MOEA) and genetic algorithms (MOGA) are commonly used to achieve a diverse and well-distributed set of solutions. WATHNET-5 houses the genetic algorithm, εMOGA, which uses the ε-dominance concept to ensure diverse and well-distributed sets of solutions are identified with relatively small computational cost (Borgomeo et al. 2016; Mortazavi et al. 2012, 2014). Starting with a random selection of options, the algorithm evaluates potential solutions in the context of WATHNET-5's underlying non-linear program. New offspring (solutions) are generated through reproduction, crossover and mutation of existing solutions, and are evaluated against older offspring. A fitness value is assigned to each solution according to the objective functions and constraint violations, and the weaker solutions are eliminated. The multi-objective optimization ends when the stopping criteria have been satisfied (e.g. when the maximum number of iterations is reached or no changes are observed in the Pareto-frontier).

The importance of multi-objective optimization in water systems planning is illustrated by Mortazavi et al. (2012), who use WATHNET-5 to manage drought security in the headworks system for Sydney, Australia. In the study, seven long-term synthetic stream flow simulations are used alongside optimization to identify optimal planning solutions for 500- and 10,000-year droughts. Different droughts produce different configurations of options, with larger droughts helping to prepare for worst case scenarios. Through multi-objective optimization, decisions can be made after considering the important trade-offs between drought security and other objectives. Using WATHNET-5 in a later study, Mortazavi et al. (2014) consider the social burden of drought emergencies alongside cost in water planning problems.

Optimization has also been used as a decision making tool in the management of riverine ecosystems to evaluate alternative management strategies against conflicting and/or harmonious objectives (Barbour et al. 2016). Setting ecological objectives are important to achieving the best possible set of solutions in multi-objective optimization. Some studies focus on achieving hydrological metrics to satisfy ecological water needs, whilst others target ecological needs directly (Horne et al. 2016). Most water resource planning frameworks use instream flow requirements or social and environmental costs as environmental indicators, however, several studies have shown that other indicators can be used successfully to evaluate the trade-offs between water system augmentation and the environment (Loucks, 2006; Dittmann et al. 2009).

3.4.4 Computing platform and data analysis

Simulations of the water system models used in this thesis were run at a daily time-step. Whilst WATHNET-5 offers highly efficient simulation, the computing power needed to perform super-ensemble driven simulations exceeded that of a standard personal computer. An Intel® Core™ i7-6600U machine with 2.6GHz processor on a 64-bit operating system was used in the model development and testing stage. The University of Oxford Advanced Research Computing (ARC) Facility was used for simulation and multi-objective optimization experiments using large scenario ensembles (Richards, 2015). The powerful computing offered by ARC was especially valuable for the research presented in **Chapter 4**, which relied on extensive simulation and resimulation experiments to ensure the planning solutions were robust to a wide range of future conditions.

Data processing, analysis and visualisation were performed using the mathematical software, Matlab (The MathWorks Inc, 2019) and R (R Core Team, 2013), and the geographic information system, QGIS (QGIS Development Team, 2016). Matlab was

chosen for its user-friendly interface, large range of tool boxes and functions, and simple programming language. R was selected for its wide range of open-source statistical packages. QGIS was chosen for its accessibility and speed of execution.

4 Selecting indicators and optimizing decision rules for long-term water resources planning

Abstract

Decision rules provide an intuitive framework for water resources planning. Having adopted a rule-based plan, decision makers can monitor critical variables in order to trigger timely adaptation actions when the variables pass their pre-determined thresholds. However, establishing a strategy that is comprised of a set of decision rules raises methodological challenges: (i) to identify observable indicators that provide reliable information about current and future change; (ii) to choose suitable statistics to characterise non-stationary time series that are germane to system performance; and, (iii) to optimize threshold levels that trigger interventions. Here we propose a methodology that addresses these methodological challenges whilst explicitly balancing expected risks of water shortages with the costs of intervention in the water supply system. The four-step framework uses a multi-objective evolutionary algorithm to search for and identify combinations of indicator-informed decision rules that govern if, when and what supply options should be included in the water resource system. The rule-based strategies are dynamically tested against an extensive ensemble of future climate and demand scenarios to examine the trade-offs between strategy cost and level of service. The framework is applied to the London water system (Thames Basin, England) using regional climate simulations to identify strategic rules for a 60-year planning period. The results demonstrate the utility of the framework, generating optimal rule-based planning

strategies. In key areas of the solution space, rule-based strategies reduce expected restriction costs on average by 13.1%, and as much as 24.1%, for a given intervention cost.

4.1 Introduction

Globally, communities face increased water stress as a result of growing demands for water and increased supply uncertainty (Bates et al. 2008; Vörösmarty et al. 2000; Vörösmarty et al. 2010). Water planners must address these issues through improved water conservation, resources coordination, and capacity expansion projects. However, uncertainties arising from climate change, population growth, changing patterns of water demand and consumption, technological advancements, and regulatory reform continue to complicate water resources planning problems (Brown et al. 2015; Wilby & Dessai, 2010). Previous research has sought to overcome these issues by identifying long- and short-term water system investment portfolios (Borgomeo et al. 2018; Borgomeo et al. 2016; Mortazavi et al. 2012), modular capacity expansion programmes (Buurman & Babovic, 2016; Hino & Hall, 2017; Jeuland & Whittington, 2014; Steinschneider & Brown, 2012; Wang & De Neufville, 2005), and optimal adaptation decision sequences (Fletcher et al. 2019; Herman & Giuliani, 2018). In these planning methodologies, plans are typically tested against a wide range of environmental, climatic, and social conditions, with an overall aim to: (i) find policies that perform satisfactorily across a wide range of future conditions (Jeuland & Whittington, 2014; Kasprzyk et al. 2013; Lempert & Collins, 2007), or against extreme future conditions (Ben-Haim, 2006; Korteling et al. 2013); (ii) discover policies that perform well in different regions of the uncertainty space (McPhail et al. 2020; Steinmann et al. 2020; Trindade et al. 2019); or, (iii) identify uncertain conditions under which policies fail (Groves et al. 2015).

Many capacity expansion projects involve large, ‘lumpy’ and inflexible capital commitments, the success of which are highly vulnerable to future uncertainties (Fletcher et al. 2017). Such investments are more cost-effective if the final decision on their implementation can be delayed until empirical evidence demonstrates with more

confidence that they are definitively needed to manage future risks of water shortages. Adaptive portfolios and policies aim to address this issue by flexibly adapting the water system as new information becomes available (Pahl-Wostl et al. 2013). In these approaches, adaptation actions respond to observed and anticipated water scarcity, risks to water supplies, and other evidence of on-going system change. Uncertainty characterisation using indicators of change provides an opportunity to avoid unnecessary and potentially irreversible investment decisions by linking adaptation actions to exogenous uncertainties, such as climate change (Fletcher et al. 2019) or changing patterns of water consumption (Di Baldassarre et al. 2018), as well as uncertainties surrounding investment options, such as infrastructure construction time (Trindade et al. 2019). A monitoring system of observable indicators and triggers ensures that adaptation actions are only taken if and when necessary, with actions being triggered when indicators of change detect the need for adaptation.

Many studies have demonstrated the value of using indicators of change to inform water resource planning and operations. In their study of risk-based adaption and planning under deep uncertainty, Haasnoot et al. (2013) propose a dynamic adaptive policy pathway framework which considers uncertainties in future political, social, technological, economic, and climate states. A monitoring system with signposts and triggers is used to detect changes to the water supply system. When the triggers are activated, the actions are deferred, expanded, abandoned or modified. Likewise, Fletcher et al. (2019) incorporate learning about future climate observations into a reservoir capacity expansion plan in Mombasa, Kenya, with results illustrating the importance of developing adaptive policies that consider conditions as they change over time. Zeff et al. (2016) propose a coupled framework for adapting long-term infrastructure sequencing and short-term drought management, using an aggregate risk-of-failure indicator to trigger adaptation actions. In

their case study example, the indicator is defined by the probability of total reservoir storage dropping below 20% of total capacity in 78 weeks. Trindade et al. (2019) use the same risk-of-failure indicator to identify cost-effective infrastructure options and short term water management policies that are robust to endogenous uncertainties in the Research Triangle of North Carolina, USA. Herman & Giuliani (2018) also use reservoir storage, alongside inflow measurements, as indicators for threshold-based operating policies for the Folson Reservoir in California, USA. The framework is designed to optimize the conditions that determine whether management actions are taken, rather than optimizing the sequence and timing of actions. The simulation-optimization approach successfully identifies optimal policies for individual future scenarios, and also robust policies that perform well across a range of future scenarios. Additional examples of indicator informed planning are presented in Kirsch et al. (2013), Steinschneider & Brown (2012), and Woodward et al. (2014).

Indicator-based planning frameworks face several methodological challenges. Principally, the planner must identify: (i) the optimal number of indicators to include in the monitoring system; (ii) the windows of observation for each indicator; and, (iii) the thresholds for individual indicators which define when an adaptation action is triggered. For some systems, an aggregate indicator such as reservoir storage (Fletcher et al. 2017; Paton et al. 2014; Trindade et al. 2017; Zeff et al. 2016) or the supply-demand gap (Erfani et al. 2018) may be used to inform planning. Yet aggregate indicators are influenced by system inputs (flow) and outputs (water use), which will likely change on different timescales and have different degrees of predictability. Separating the effects of these variables could lead to improved prediction of future water system performance when multiple uncertainties exist. Similarly, plans using only one indicator of change (Hui et al. 2018; Steinschneider & Brown, 2012) may underperform compared to plans with multiple

indicators that target different sources of uncertainty. This effect could be especially important for spatially heterogeneous water systems with regions that are influenced by more than one source of uncertainty.

In spite of the evidence in favour of indicator-based approaches to water planning, many of the studies discussed above do not offer a clear process for indicator selection. Instead, indicator choice is judgement-based and may therefore not optimally select the indicators that are most likely to achieve the desired outcomes in the long run. Several studies have shown that indicators must be chosen systematically, scientifically, and evaluated a-priori against selection criteria. Galelli et al. (2014) argue that variables should be selected based on their usefulness for predicting a system outcome of interest, proposing the Input Variable Selection (IVS) framework to identify candidate observable variables that characterise the relationship between input-output variables in predictive models. Raso et al. (2019) propose that indicators should be selected based on four measures: relevance, observability, completeness, and parsimony. Indicator relevance features heavily in indicator selection frameworks, referring to the influence, or relationship, of the indicator on adaptation policy success. A relevant indicator should represent emerging trends of uncertain drivers in the underlying system, whilst remaining closely related to system performance and plan success. Observability measures the amount of data required to calculate the indicator, with high observability meaning that a good estimate of the indicator can be obtained with relatively little data. Completeness represents the combined ability of selected indicator variables' ability to represent critical uncertainties in the system being modelled, with a greater number of indicators being more likely to achieve high completeness. The importance of completeness is demonstrated by Giuliani et al. (2015), who use simulation and an evolutionary algorithm to identify variables best suited to inform reservoir operations of the Hoa Binh Reservoir in Vietnam. In their investigation,

historical and real time observations of rainfall, river flow and water levels are used to design reservoir operating policies. The performance of the indicator-based policies is compared to Perfect Operating Policies (POP) designed using perfect foresight, with results showing that the policies with multiple observable variables achieve the best performance relative to the POPs. Finally, Raso et al. (2019) state that the selected set of indicators should be parsimonious, with an ability to detect important ongoing changes without increasing the dimensionality of the planning process. To achieve parsimony, no two indicators should describe similar or identical features of the system being modelled (Raso et al. 2019). As Herman et al. (2020) report, analysing and optimizing flexible planning systems can be conceptually challenging and computationally expensive. Thus, selecting a parsimonious monitoring system helps to avoid unnecessary complexity which may render the computational problem intractable.

Scenario discovery has also been used as a mechanism to identify informative indicators for adaptive management actions, with studies adopting discovery methods to find important sub-spaces within the problem uncertainty space that influence policy performance (Kwakkel, 2019). Groves et al. (2015) use a Robust Decision-Making framework to identify early warning indicators emerging from scenarios of future conditions in the Metropolitan District of Southern California, with an aim to use indicators to prevent the current planning strategy from failing to meet its goals. In contrast, Trindade et al. (2019) adopt scenario discovery to detect key drivers of system performance and robustness under indicator informed water resources planning. Lastly, Fletcher et al. (2017) combine simulation and scenario analysis to identify key uncertainties that will inform learning over time. The planning framework is used to develop historic planning portfolios for Melbourne, Australia, considering uncertainties in

reservoir inflows, population growth rate, electricity prices, water shortage penalty values, and demand when implementing real adaptation options.

Evidently, a range of methodologies exist to identify the best indicators of change for water resources planning. Yet few indicator selection methodologies go on to define the threshold an indicator must exceed for an adaptation action to be triggered. Within water resources, triggers are commonly adopted in short-term feedback control loops, such as those defining reservoir operating policies (Giuliani et al. 2015), flood control and conservation actions (Herman & Giuliani, 2018), and water use restrictions (Borgomeo et al. 2016; Mortazavi-Naeini et al. 2014). Other studies focus on defining thresholds to trigger long-term permanent capacity expansion infrastructure, with many planning frameworks using Multi-Objective Evolutionary Algorithms (MOEA), or Genetic Algorithms (MOGA), to optimize threshold values for specific adaptation actions. For example, Mortazavi-Naeini et al. (2015) and Zeff et al. (2016) examine the success of algorithm generated trigger-based adaptation policies against ensembles of synthetic streamflow scenarios. Likewise, Trindade et al. (2017) use a MOEA and Many-Objective Robust Decision Making framework to identify risk-of-failure indicator thresholds for planning portfolios in the Research Triangle region of the US, demonstrating the importance of evaluating adaptation action triggers against a wide range of future hydrologic, demand, financial, and infrastructural uncertainties. Robinson & Herman (2019) present an alternative approach to defining adaptation triggers that does not rely on MOEAs, developing a data-driven quantitative framework to identify planning thresholds based on vulnerable scenarios within ensemble projections. As the authors acknowledge, however, the study fails to consider more than one type of indicator and does not apply the methodology to a real-world planning problem.

The discussion above reveals a scarcity of methodologies that combine indicator selection and threshold definition for long-term adaptation planning under 21st Century uncertainties. This paper presents a step-by-step framework to overcome this gap, developing indicator informed adaptive water resources planning strategies that balance the cost of adaptation, aggregated over time, against the benefits of adaptation, defined by the reduction in expected risk of water shortages. We first use simulation and linear regression to identify a set of candidate indicators from a larger pool of indicators, based on the indicator's ability to predict future risk of failure in the water supply system. Next, multi-objective optimization is used to define water resource planning strategies. Each strategy contains a set of decision rules, with each rule containing one or more candidate indicator(s), optimized indicator threshold value(s), and a corresponding adaptation action which is triggered if the indicator(s) surpass the optimized threshold(s). The strategies generated in the multi-objective optimization search are Pareto-optimal against a range of future uncertainties. The position of Pareto-optimal solutions in the objective space, relative to baseline 'fixed' plans, is used as a measure of the indicator's contribution to improving system performance. The best indicators of change are selected based on their ability to produce water resource strategies and adaptation actions that minimise (in a Pareto-optimal sense): (i) financial costs of operating and adapting the water system; and, (ii) the expected risk of water restrictions, across a range of future conditions. Further validation of indicator selection is provided in Step 4 through out-of-sample simulation, which tests selected strategies against a wider range of future conditions. A summary of the framework to identify decision rule-based water planning strategies is presented in **Figure 4.1**.

The framework is applied to a water planning problem in the London water system (Thames Basin, England), using indicators of climate and demand uncertainties to inform

long-term adaptation actions. The rule-based strategies are optimized against risk-based performance metrics that consider adaptation cost and observable water use shortages, having been tested with a large ensemble of climate-change driven hydrological flows and population-driven demand projections. The strategies are categorised as risk-based because they are evaluated against their ability to reduce the frequency, severity and duration of water restrictions and the associated impacts, which in this case are valued as financial costs (Borgomeo et al. 2016). The results show that user-oriented decision rules, consisting of observable indicators and triggers, provide practical guidance to decision makers who are faced with uncertainties concerning future states of the world.

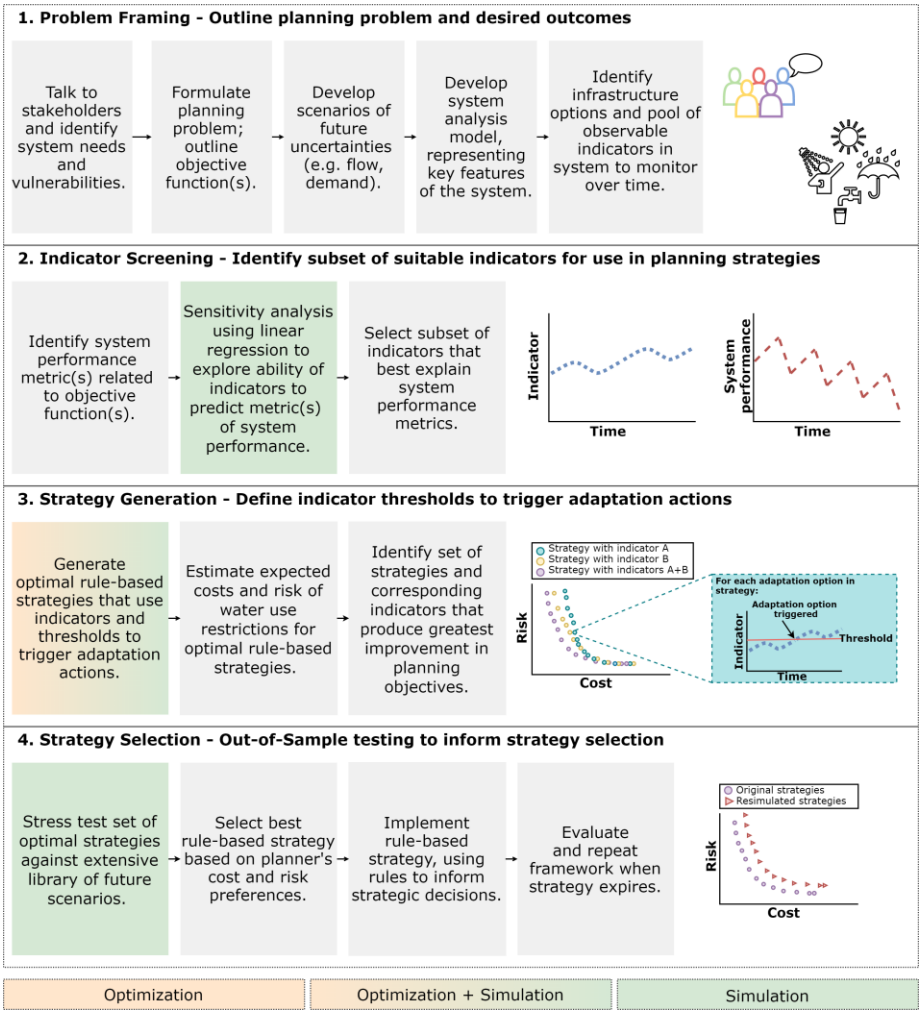


Figure 4.1. Framework to identify rule-based strategies to inform water resource planning.

4.2 Methods

4.2.1 Step 1 – Problem framing

4.2.1.1 Stakeholder dialogue

Planning for water systems requires well defined aims, objectives, and clear communication between stakeholders (Poff et al. 2010; Trindade et al. 2017). Precise communication is especially important for optimization-based planning approaches which are influenced by objective functions (Quinn et al. 2017), so this stage requires stakeholders to clearly define the objectives for their system and outline the planning problem to solve. Common objectives in water resources planning under uncertainty include: (i) minimising financial costs of the water system, including capital and operating costs; (ii) minimising environmental impacts (including greenhouse gas emissions) and where possible enhancing the aquatic environment; and, (iii) minimising the risk of an event occurring that may negatively impact water users. The proposed framework considers a set of z planning objectives, $W = \{w_1, \dots, w_z\}$. The first planning objective aims to minimise the financial costs associated with construction and operation of the water resource system. Subsequent objectives are at the discretion of the water planner, but should seek to minimise one or more risk metrics inherent to the planning problem. The risk metrics may relate to the expected risk of water shortages, the economic risk of flood damages, or water quality risks. This study uses the risk metric developed by Borgomeo et al. (2018), which estimates the expected cost of water use restrictions, as a function of the frequency, duration, and severity of restrictions imposed throughout the planning period. The metric is classified as risk-based according to criteria by Hashimoto et al. (1982), and explicitly considers the economic consequences of restrictions of differing severities. The planning problem is framed as multi-objective because water

managers frequently face planning decisions that trade-off reductions in risk achieved by water system adaptation against the cost of adaptation investments (Garrick & Hall, 2014).

In addition to the planning objectives, stakeholder discussions should outline operational constraints in the water supply system, such as environmental flow limits, water withdrawal licences, minimum reservoir releases, and target pumping levels.

The question of which options to include in the search for optimal planning strategies requires applying experience and creativity to particular contexts. Consultation with stakeholders and review of analogous cases in different river basins will help to identify a wide range of candidate options. The set of adaptation options are denoted as $A = \{a_1, \ldots, a_g\}$, where g is the total number of options to consider. This framework focusses specifically on capacity expansion options and demand saving schemes, but could also be used to define indicator-informed operational rules that work on shorter planning timeframes.

Dialogue between the water planner and stakeholders can also inform the identification of indicator variables to be used in the adaptation monitoring system, thanks to local knowledge about the system vulnerabilities. These discussions could point towards use statistics of river flow, precipitation, temperature, population change, elapsed time, and/or water use as decision-relevant indicators.

4.2.1.2 System model

A system model is used to simulate the impact of water planning strategies and corresponding adaptation actions under changing future conditions. Simulation answers the 'what if' questions of system operation (Loucks et al. 2005), allowing the planner to simulate the movement of water through the system under different sets of driving factors. Key features of the water system should be represented within the system model, including

inputs (surface and groundwater withdrawal points), outputs (demand centres), system operation, planning options, and capital and operating costs of adaptation actions. Our framework requires that the system model can represent outcomes of interest to decision makers, such as water shortages of varying frequency, severity and duration (Hall & Borgomeo, 2013), or indicators of water quality (Mortazavi-Naeini et al. 2016). Whilst less-computationally intensive models could be used for initial assessment of planning options and adaptation policies (Haasnoot et al. 2014; Hall et al. 2016), a model which fully represents operational complexities of the water system is necessary to examine the performance of candidate water planning strategies (Borgomeo et al. 2018).

Consistent with several other water planning studies, this framework uses a discrete event simulation model to represent the water supply system (Dobson et al. 2020; Mortazavi-Naeini et al. 2015). In simulation, decision rules are consulted at discrete time-steps to inform adaptation actions. These actions are represented by discrete values, which pertain to individual planning options identified in stakeholder discussions, their associated yields, and infrastructure construction lead times. The use of discrete values reflects common water utility planning approaches, which pre-select features of candidate adaptation actions based on economic, social, and geographic constraints (Herman et al. 2020).

4.2.1.3 Scenarios of uncertainty

Extensive simulations of the system model are required to evaluate the performance of long-term planning strategies against future uncertainties. Strategies are simulated against an ensemble of k scenarios denoted by $X = \{x^1, \dots, x^k\}$. A scenario x^i is comprised of time series of future conditions that are input into the system model, and is denoted by $x^i = \{x_t^i : t = 1, \dots, q\}$, where t represents the time-step (i.e. day, month, year) in a time

series of length q. With some abuse of notation, we herein refer to scenario x^i as scenario i. The system model described in **Section 4.2.1.2** uses the ensemble of future scenarios as inputs, simulating state variables in the system, such as river flows, diversion volumes, reservoir levels, and volumes of water delivered to users.

The framework presented here targets exogenous uncertainties in the water supply system arising from climate change-driven hydrological projections and population-driven water demand forecasts. However, the framework could consider other uncertainties that can be defined using an a priori ensemble, such as hydrological modelling uncertainties (Ajami et al. 2008), uncertainties concerning infrastructure construction cost and lead times (Trindade et al. 2019), and land use change uncertainties (Kwakkel et al. 2015).

4.2.2 Step 2 – Observable indicator screening

4.2.2.1 Quantifying expected risk in a no adaptation future

We require the set of indicators used in the rule-based strategies to be parsimonious, as this helps to reduce monitoring costs and reduces the complexity of the planning problem. At the same time the indicators need to efficiently represent the factors that determine future system performance (Raso et al. 2019). A detailed examination is necessary to identify candidate indicators from the larger pool of stakeholder suggested indicators, and to identify the most appropriate statistics of candidate indicator variables. For example, low flow statistics may feature in discussions as an ideal indicator variable for the target water system, but the severity, type of statistic, and time-window over which to observe the statistic will be difficult to define through intuition alone. Given that some candidate indicators will have high variability, we wish to select statistics (e.g. moving averages) that are sensitive to changes and salient to system performance whilst being relatively stable i.e. having low sampling variance. Ultimately, the indicators should not be unduly

influenced by random fluctuations and at risk of triggering false-positive adaptation (Robinson & Herman, 2019).

The process presented in Step 3 adopts multi-objective optimization to identify the indicators that produce the greatest improvement in objective performance, relative to the performance of 'fixed' plans (described in **Section 4.2.3.3**). However, this entails an expensive two-stage optimization, requiring optimization of decision rules and strategies in a large ensemble of scenarios, for every candidate indicator. Given the complexity of the system and the size of the option space for both indicators and strategies, this is not computationally feasible. Therefore, an empirical analysis is adopted in Step 2 to narrow down the set of indicators to take forward into Step 3. In this step, we identify indicators that enable the water planner to make better adaptation decisions in the future, where 'better' is measured in terms of the objectives outlined in **Section 4.2.1.1**. Because this framework assumes the cost of adaptation is known without uncertainty, indicator selection is based on the planning objectives that minimise future risks in the water system. If the world was stationary and we had extensive measurements of historical system performance, we could accurately estimate present-day risk using past observations. We could also conclude that, without adaptation, this estimation of risk would remain the same in the future. As this is not the case, we use simulation to predict future risk in a 'no adaptation' future by using observable indicators of change.

First, the system model developed in **Section 4.2.1.2** is run under the ensemble of scenarios, X, to estimate performance metrics directly related to the risk-based objective function(s). For each simulation run under scenario i, a performance metric, p_t^i, is estimated at each time-step t. An example performance metric could estimate the daily expected cost of water-use restrictions, or the probability of flooding, at time t. No adaptation actions are implemented in these simulations; instead, water demand is met by

supply from existing features of the water system. It is for this reason that a performance metric related to the cost-based objective function need not be considered.

Candidate indicators are also calculated for each time-step t in simulation of scenario i. Indicators could use statistics of river flows and demand, or simulated measurements of existing water supply infrastructure, such as reservoir levels. o_t^i represents an observed indicator value, recorded at time t, in scenario i. O_t denotes the set of all possible observation indicators identified in stakeholder discussions to be observed at time t.

4.2.2.2 Select subset of indicator variables

Ordinary least-squares regression is used to quantify the strength of the relationship between an observable indicator, o_t^i, and the risk metric, h_t^i, which is calculated as $h_t^i = \sum_j^q p_j^i$, where $j = t + 1$. Here, h_t^i represents the aggregated risk at time t remaining in scenario i. Regression models are considered in the form $h_t^i = \beta_0 + \beta_1 o_t^i + \epsilon$, where β_0 is the intercept, β_1 the regression coefficient for indicator o_t^i, and ϵ the error term. Models can be built with multiple indicators to investigate the combined ability of indicators in predicting future risk. To achieve a parsimonious monitoring system and avoid selecting redundant variables, indicators should be considered together only if they represent different sources of uncertainty. Indicators with different observation periods should also be considered. The desired indicator should have a long enough observation window to screen natural variability, but not so long that it fails to identify non-stationarity in indicator trends. Models using indicators with different time windows should only be compared if they use observations and simulation output from identical time periods. Therefore, two regression models using indicators with observation periods spanning 5

and 10 time-steps should only be compared if they consider identical time series for o_t^i and h_t^i that start at $t = 11$.

Individual indicators (and combinations of indicators) are selected based on several criteria. First, indicators are eliminated if *p-values* for coefficient estimates of each model term are not significant at the 5% significance level. *p-values* are derived from t-statistic tests that test the hypothesis that the coefficient is equal to zero. Second, regression models are ranked according to root mean squared error (RMSE), which represents the standard deviation of the error distribution. Models with the smallest RMSE are assumed to have the greatest predictive ability. The coefficient of determination (R-squared) could also be used to rank the regression models, whereby larger R-squared values indicate greater predictive ability.

The candidate indicators (or combination of indicators) that perform best according to the selection criteria outlined above are used in Step 3 to generate rule-based adaptation strategies. If multiple indicators exhibit similar predictive abilities, both can be taken forward into Step 3 for further screening.

4.2.3 Step 3 –Strategy generation

This step serves two purposes. First, it defines thresholds for the indicator variables identified in Step 2. Each threshold is individual to an adaptation option identified in Step 1. Second, it provides a mechanism to identify the best indicator variables to inform adaptation under future uncertainty.

4.2.3.1 Strategies and decision rules

As established previously, observable indicators are monitored over time and used to inform adaptation decisions in the future. To trigger an action, an indicator must cross a

pre-determined threshold. When considered together, an observable indicator, threshold, and corresponding adaptation action describe a decision rule. A planning strategy contains one or more decision rules, with each rule characterising the implementation of individual adaptation actions (**Figure 4.2**). A planner follows a planning strategy when adapting their water system over the planning horizon.

Strategy n is defined as $s^n = \left\{b_{a_1}^n, \dots, b_{a_g}^n\right\}$, where b_a^n represents the decision rule that describes the criterion for when infrastructure option a should be triggered. Each infrastructure option has a construction lead time (m_a) and capacity that the option is built to (c_a). In this study, sources of financial (i.e. bond terms, interest rates) and logistical uncertainty (i.e. construction disruptions) that may impact option lead times and yield are not modelled. We recognise this as a limitation of the proposed framework; future work could explore the role of these uncertainties on strategy success.

We consider decision rules in the conditional–go form (Garstka & Wets, 1974), where a rule with one indicator may be of the form: IF *"observed indicator exceeds threshold value"* THEN *"build infrastructure option a with capacity c_a, with the option operating functionally after the lead time m_a has elapsed"* ELSE *"do nothing"*. If indicators are expected to display oscillatory behaviour, it may be necessary to use multi-indicator decision rules in planning strategies. For many cases, an indicator based on elapsed time will help to avoid adaptation actions being triggered as a consequence of an early random shock that is not representative of the long-term trend. A multi-indicator decision rule may be of the form: IF *"observed indicator 1 exceeds threshold value 1"* AND *"observed indicator 2 exceeds threshold value 2"* THEN *"build infrastructure option a with capacity c_a, with the option operating functionally after the lead time m_a has elapsed"* ELSE *"do nothing"*.

Figure 4.2 presents the formal notation for a one indicator decision rule, $b_{a_1}^n$. In the figure, $u_{a_1}^n$ represents the threshold, specific to Strategy n, that the observable indicator o_t^i must exceed in order to trigger option a_1. The inequality used in the decision rule is determined by the anticipated direction of change of the indicator. If the indicator is expected to increase over time, the rule will be in the form $u_a^n \leq o_t^i$; while if o_t^i is predicted to decrease the condition is $o_t^i \leq u_a^n$. We assume that an option a cannot operate functionally until the lead time m_a has elapsed and the time-step t exceeds the assigned start date d_a^i. Upon meeting this criteria, the active capacity of option a, $v_{t,a}^i$, is set at the option capacity c_a defined in Step 1.

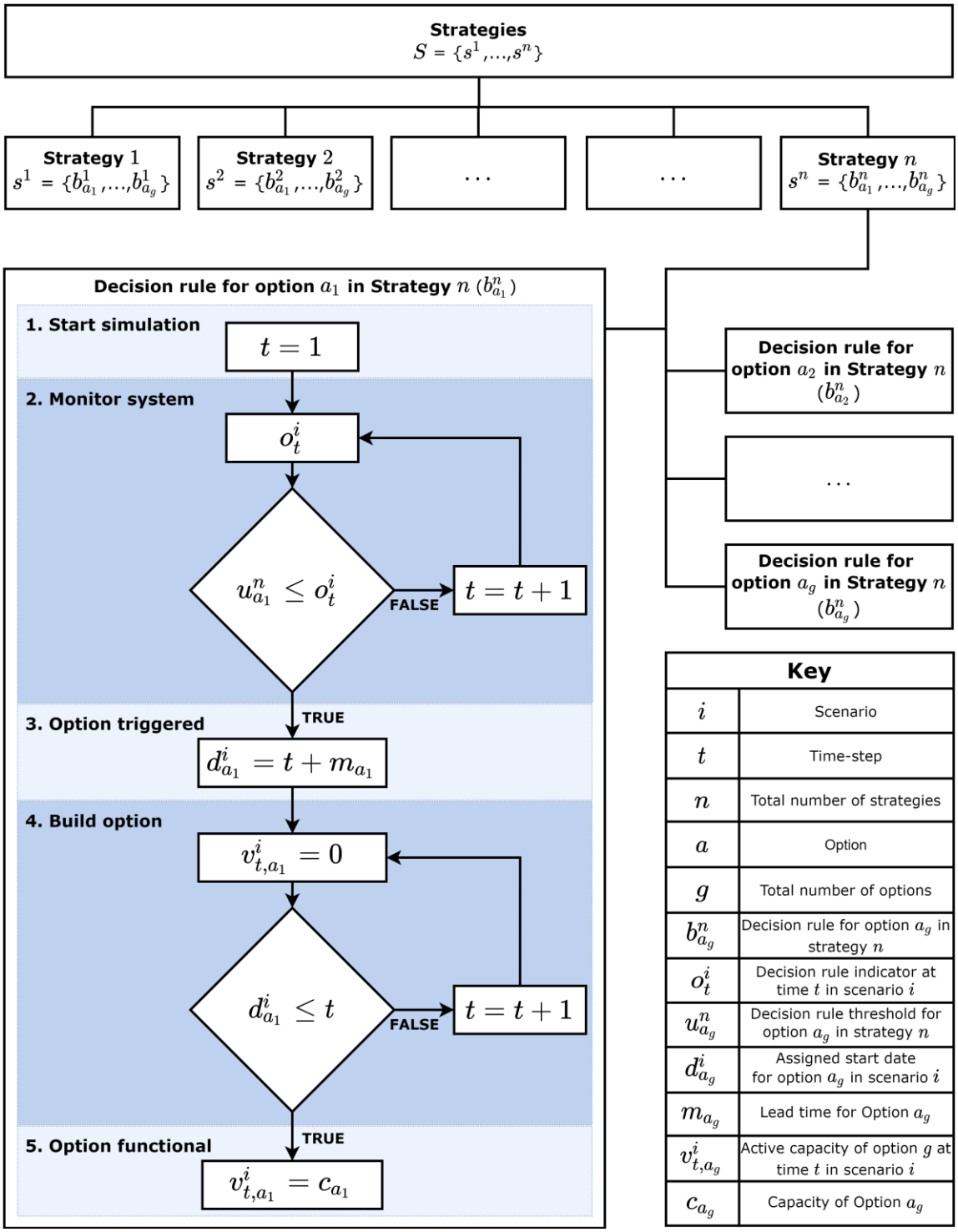


Figure 4.2. Hierarchical structure of planning strategies, decision rules, and features of a decision rule.

4.2.3.2 Threshold definition and optimization procedure

The thresholds, u, assigned to individual decision rules in a strategy s are identified using simulation and multi-objective optimization tools. Here, the system model uses an optimization module which calls simulations in parallel. The optimization procedure uses an ε-multi-objective genetic algorithm (εMOGA) to search for the set of Pareto-optimal strategies S^* from S, defined according to the objective functions $W = \{w_1, \dots, w_z\}$. εMOGA follows the ε-dominance concept, which allows one non-dominated solution (strategy, s) to occupy a hyperbox of size ε in the objective space (Deb et al. 2006; Laumanns et al. 2002). A solution ε-dominates another solution if it performs better in at least one dimension of the objective space. MOGAs and MOEAs are ideal for this application because the objectives do not need to be weighted (a priori), as solutions are selected after the trade-offs are realised (a posteriori) (Hurford et al. 2014).

The multi-objective optimization search starts with an initial population of solutions. Each solution contains candidate threshold values that govern when an option is triggered in simulation. In the first iteration of the optimization procedure, simulation is used to estimate the performance of solutions in the initial population when simulated against the set of uncertainty scenarios, X. For each solution the expectation of objective values across ensemble X are estimated $W^{s,X} = \{\frac{\sum_{i=1}^{k} w_1^{s,i}}{k}, \dots, \frac{\sum_{i=1}^{k} w_z^{s,i}}{k}\}$. The performance of a solution ($W^{s,X}$) is compared to other solutions in the initial population, and the ε-non-dominant solutions are moved to an archived population of non-dominated solutions. In subsequent iterations of the optimization procedure, new generations of solutions are simulated against ensemble X. Threshold values in a new solution are created through mutation, crossover, and inversion of existing thresholds in two parent strategies, whereby one parent is randomly selected from the archive population, and the other from the current population. The offspring solutions are accepted into the archived population if the

solution: (i) ε-dominates another solution in the archived population; or (ii) the offspring occupies an empty hyperbox along the frontier of solutions. In the first case, the new solution replaces the dominated solution and the size of the archive population stays the same. In the second case, the size of the population increases in size. If an offspring is not accepted into the archive population, it is added to the current population if it dominates one or more current solutions in the objective space. The offspring is rejected if it is dominated by any solution in the current population.

The water planner must stipulate the criteria for terminating the solution search. Typically, the stopping criteria specifies the maximum number of iterations permitted in the optimization search, or defines the minimum number of iterations which see no improvement in the archived ε-non-dominated solutions.

4.2.3.3 Baseline 'fixed' plans

As indicated in **Section 4.1**, multi-objective optimization is used to identify the indicator variables that produce the greatest improvement in adaptation portfolio performance relative to 'fixed' plans. The 'fixed' plans are generated following the optimization process outlined in **Section 4.2.3.2**, using objective functions W, uncertainty scenarios X, and set of infrastructure options A. The 'fixed' plans specify the precise times at which options are implemented, whereby an option is triggered if a rule of the following form is satisfied: IF *"current time-step exceeds time threshold"* THEN *"build infrastructure option a with capacity c_a, with the option operating functionally after the lead time m_a has elapsed"* ELSE *"do nothing"*. The 'fixed' plans are akin to traditional water resources plans (Beh et al. 2014; Borgomeo et al. 2018, 2016; Jeuland & Whittington, 2014), which identify the specific time of implementation (i.e. year) for individual planning options. The 'fixed' plan is an appropriate counterfactual to the rule-based strategies because it offers no

flexibility under future uncertainties. Unlike the strategies, 'fixed' plans build an option in the same time-step for all scenarios, regardless of realised conditions.

4.2.3.4 Indicator selection

Indicator selection is conducted by comparing the Pareto-optimal frontier of the 'fixed' plans against the frontiers of the Pareto-optimal planning strategies. The frontier that produces the largest hypervolume improvement in performance across the objective space, relative to the 'fixed' frontier, signposts the most suitable indicator (or combination of indicators) for the planning problem.

4.2.4 Step 4 – Strategy testing

Upon selecting the indicators and corresponding Pareto-optimal frontier of rule-based strategies, the planner must deliberate upon which strategy to choose on the Pareto frontier (Deb, 2001). Step 4 uses an out-of-sample ensemble of scenarios X^* to stress test candidate strategies from the selected Pareto-optimal frontier. The ensemble of scenarios X^* contain a wider range of the same uncertainty conditions represented in ensemble X. Out-of-sample simulation is important as the εMOGA solutions may be over-fit to the scenarios used in the optimization procedure (Herman et al. 2020), and therefore risk being vulnerable to a wider range of uncertainty not necessarily captured in the ensemble of uncertainty scenarios X (Kasprzyk et al. 2013). We stress that this step is designed to provide additional information on candidate planning solutions to the water planner. The out-of-sample simulation can be used to test candidate strategies along the frontier, but final selection should be based on the water planner's cost and risk preferences.

4.3 Case study and application

4.3.1 Problem framing

4.3.1.1 Background

The Thames Basin case study has been widely applied in the decision making literature (Erfani et al. 2018; Huskova et al. 2016; Kingsborough et al. 2016; Murgatroyd & Hall, 2020). The case study is used here to illustrate the benefits of incorporating indicator-informed decision rules in long-term planning for regions subject to significant supply and demand side uncertainties.

In England and Wales, water companies' water resource management plans are published every 5 years and outline a "secure and sustainable set of options to supply [your] customers with water over the long-term" (Environment Agency, 2018, p.1). We apply our method to the London water resource zone (WRZ), operated by Thames Water Utilities Ltd. Thames Water's 2019 water resource management plan revealed that increases in demand from a growing population and increased drought risk threaten the supply-demand balance, however how these threats will grow in the future remains uncertain. This region is chosen because we believe the uncertain features in the Thames Water supply system can be monitored using the proposed rule-based framework to provide key information for the water planner and improve long-term decision making under uncertainty.

The London WRZ covers an area of 9948km^2 and supplies 3.7 million households (Thames Water, 2019a). Water is principally supplied from direct abstractions from the River Thames to impounded reservoirs, with additional water supplied from the underlying chalk aquifer. The Lower Thames Operating Agreement regulates the operation of the London water system, with abstraction limits and environmental flows restricting the amount of water that can be withdrawn from rivers and reservoirs in the system. The Lower

Thames Operating Diagram (**Appendix A1**) defines the levels in which total London reservoir storage must fall below to justify restrictions on water users. The severity of restrictions increases from Level 1 to Level 4 and the water company has targets for the frequency with which such restrictions may be imposed.

4.3.1.2 Scenarios of future conditions

Uncertainty is incorporated into the planning framework by using an ensemble of scenarios of possible futures. In consultation with the water company and results from previous research in the Thames study region (Borgomeo et al. 2018, 2016) we focus upon uncertainties in water demand and water availability, which are the main determinants of the reliability of water supplies.

4.3.1.2.1 Climate

Advances in climate modelling have led to large ensembles of climatic conditions, each forecasting the different pathways the climate may evolve throughout the 21st Century. Individual ensemble members typically represent a realisation of uncertainty in climate model projections and human forcing factors, and so naturally fits within the scenario framework introduced here.

Simulations of time series of weather variables for possible future climate scenarios were obtained from the Weather@Home (W@H) modelling framework (Guillod et al. 2017, 2018; Massey et al. 2015), which consists of a global climate model (HadAM3P) with nested regional climate model (HadRM3P), and is driven with historic (HadISST) and projected (CMIP5) sea surface temperatures (SST) and sea ice. W@H is a 'citizen science' project that benefits from the unused computer power of thousands of participants to generate large ensembles of climate model runs. Previous work has used

W@H to investigate sea surface temperature driven extreme weather events (Haustein et al. 2016), heat related mortality (Mitchell et al. 2016), flood damage (Schaller et al. 2016), and national scale drought (Dobson et al. 2020; Rudd et al. 2019). The W@H climate sequences have also been used to showcase the risk-based planning framework developed by Borgomeo et al. (2018).

The Weather@Home dataset contains precipitation (P) and evapotranspiration (PET) time series at a 25km resolution, which is then downscaled to 5km resolution. In the downscaling process, P is bias corrected using a linear approach with monthly bias correction factors. A complete description of the bias-correction methodology, validation process and results is presented in Guillod et al. (2017, 2018). The full dataset of downscaled P and PET is grouped into three ensembles:

- 100 realisations of the Baseline period (1975-2004), generated using different initial atmospheric conditions, and historic SST and sea ice records from HadISST (Rayner et al. 2003; Titchner & Rayner, 2014);
- 100 realisations of the Near Future period (2020-2049), generated using 50th percentile SST and sea ice projections (CMIP5, (Taylor et al. 2012)) under Representative Concentration Pathway (RCP) 8.5 (Meinshausen et al. 2011);
- 100 realisations of the Far Future period (2070-2099), generated using 50th percentile SST and sea ice projections under RCP8.5.

Because RCP8.5 represents the upper bound of projected global emissions scenarios, the future W@H datasets contain synthetic drought events that are more severe than have been observed in the historical record (Guillod et al. 2018). This makes the weather sequences ideal for water resources impact assessments and portfolio planning that consider the risks of system failure under extreme events.

4.3.1.2.2 Hydrology

Flows in the Thames Basin were simulated using the rainfall-runoff modelling framework, DECIPHeR (Dynamic fluxEs and ConnectIvity for Predictions of HydRology) developed by Coxon et al. (2019). DECIPHeR is well suited to this study as it is able to simulate flows for across multiple spatial scales efficiently and quickly, and has been shown to perform well against multiple evaluation metrics when used to simulate historical flows at 1366 river flow gauges across Great Britain (Coxon et al. 2019).

DECIPHeR has previously been used to generate ensembles of historical and future naturalised flows for 338 catchments across England and Wales (Dobson et al. 2020). In Dobson et al.'s study, historical flows were first simulated using daily observed P (Tanguy et al. 2019), PET (Robinson et al. 2016), and 10,000 different model parameter sets (Coxon et al. 2019). The ensuing flow ensemble was evaluated against daily naturalised flows supplied by England's Environment Agency, and the best parameter set for each catchment was identified according to NSE and logNSE scores. Future flows for each of the 338 study catchments were simulated using the best parameter set for each catchment and downscaled W@H P and PET weather sequences. This study follows the same hydrological modelling framework outlined by Dobson et al. (2020), using the best performing DECIPHeR parameter set for catchments in the Thames Basin to simulate future flows. For the purpose of this study, the 30-year Near and Far Future flow scenarios are transformed into 100 longer 80-year transient time series, as explained in **Appendix A2**. Further information about the behaviour of the transient DECIPHeR flow ensemble is provided in **Appendix A3.**

4.3.1.2.3 Demand

Uncertainties in demand forecasts are a consequence of uncertain changes in population (Erfani et al. 2018; Jeuland & Whittington, 2014), economic growth (Vörösmarty et al. 2000), and trends in water consumption (Fletcher et al. 2017; Trindade et al. 2017). In catchments where domestic water supply is the dominant water use, like the one considered in this paper, demand can be parsimoniously represented through a product of population and per capita consumption, both of which are uncertain.

One hundred demand scenarios are generated for the London WRZ, which is represented by a demand node within the system model. Baseline forecasts of water demand (Ml/d) from Thames Water's WRMP19 (Thames Water, 2019a), containing data on per capita consumption projections (Environment Agency, 2019b), were scaled using ten population forecasts for the London area from 2014 to 2039 obtained from the Office for National Statistics (Office for National Statistics, 2016). The forecasts are lengthened using linear extrapolation. A further 90 demand scenarios were generated by scaling with a sample from a uniform distribution on the range [0.9, 1.1]. For the remaining demand nodes in the model, ten scenarios of municipal water demand were estimated using the dry year annual average distribution input at water resource zone level and scaled according to Thames Water water resource planning tables and demand profiles (Thames Water, 2019a). Additional information on the London WRZ demand ensemble is presented in **Appendix A4.**

4.3.1.2.4 Ensemble

Each demand scenario is randomly coupled with one of the 100 DECIPHeR transient flow scenarios, forming the ensemble X. The out-of-sample ensemble, X^*, is constructed in the

same way, but the ensemble size is increased to 1000. **Appendix A5** illustrates the distribution of flow and demand conditions in ensemble X and X^*.

In this application, the demand scenarios are assumed independent of climatic conditions; an assumption which is warranted by an earlier study of the impact of climate change on water consumption in the Thames water supply area (HR Wallingford, 2012). The authors recognise that this assumption may not be true for other regions, and stress that water planners should consider the impacts of climate change on water demand in their own water supply systems when constructing scenarios of uncertainty.

4.3.1.3 Planning options

Five infrastructure planning options are considered in this study (**Table 4.1**). The planning options are akin to the supply side options developed by water managers in Thames Water (Thames Water, 2017). As some options have multiple possible capacities, the optimization search is constrained to prevent the implementation of the same option twice in one strategy. Each option has a construction lead time which determines the elapsed time between triggering an option and an option becoming operational. The planning options are assigned two types of financial cost: the net present value of capital expenditures (capex, CP) denotes the cost incurred when an option is first triggered and is specific to the option capacity; operational expenditure (opex, OP) represents the cost of operation for each day the option is utilised (after the construction lead time has elapsed).

Four water demand management policies, 'reduced', 'maintain', 'effective' and 'enhanced', are also included in the search for optimal strategies. The schemes are fixed in time and represent increasing levels of demand reduction and their associated costs. Additional information on the demand management policies is provided in **Appendix A6.** We do not apply flexible rules to demand management because the schemes are initiated

on day one of the strategy, regardless of scenario. This modelling choice is consistent with the expectation that water companies should take actions to reduce water demands and improve water use efficiency both now and into the future (HM Government, 2018).

Table 4.1. Supply side options included in the search of optimal strategies and fixed plans for the Thames Water System.

Option number	Option Name	Option Lead Time (year)	Capacity (Ml/d)	Total Capex (£k)	Total Opex (£k/y)
Option 1	**Transfer** Deerhurst to Cricklade	7	0, 100, 300, 600	0-47268	0-3128
Option 2	**Direct River Abstraction** Teddington	7	0, 300	6601	702
Option 3	**Desalination** South Thamesmead to Coppermills	3	0, 150, 300	0-12850	0-832
Option 4	**New Reservoir** Upper Thames Catchment	12	0, 151, 283	0-96875	0-3262
Option 5	**Reuse** Beckton	2	0, 100, 150, 300	0-39370	0-4307

Source: Thames Water (2017)

4.3.1.4 Planning objectives

We consider two planning objectives for the case study. Objective function $f(1)$ minimises the expected total present cost of adaptation, averaged across the scenarios of uncertainty in ensemble X:

$$f(1) = min \frac{\sum_{i=1}^{k} \sum_{t=1}^{q} \left(\frac{CP_t + OP_t}{(1+r)^t} \right)}{k}$$

where k represents the total number of scenarios, q the total number of time-steps in a scenario, CP_t and OP_t the capital and operating expenditures incurred at the time-step t, and r the discount rate, set at 4.5% in this case study example. This rate is consistent with the HM Treasure Green Book discount rates (Thames Water, 2019a). Objective function

$f(2)$ minimises the expected restriction cost of Level 3 and Level 4 water use restrictions, averaged across the scenarios of uncertainty in ensemble X:

$$f(2) = min \frac{\sum_{i=1}^{k} \sum_{t=1}^{q} \sum_{l=3,4}^{l} (E_l)_t}{k}$$

where $(E_l)_t$ represents the expected cost incurred from a water use restriction of level l in time-step t. We use the economic estimates of the cost of water restrictions defined by Borgomeo et al. (2018), who count the total days of restrictions imposed in a scenario and weight them according to their severity using a relative weight derived from surveys of customer willingness to pay to avoid restrictions. Level 4 (l_4) events are 40 times the expected daily economic losses (E) of Level 3 (l_3) events, costed at £282M and £6.8M per day, respectively (Lambert, 2015). Economic estimates for Level 1 and Level 2 restrictions are orders of magnitude less than Level 3 and 4 restrictions and thus excluded from this study. As stated previously, $f(2)$ is considered a risk-based metric as it considers the frequency, severity and economic consequences of an event of interest to water managers.

4.3.1.5 System model and optimization procedure

This study uses WATHNET-5, a simulation model of water withdrawals, storage and releases with an in-built multi-objective optimizer (Kuczera, 1992). The model represents a water resource system as a network of arcs (conduit and stream) and nodes (reservoir, demand, river inflow, groundwater, junction and waste). The Thames model used here contains nine demand nodes, twelve surface water nodes, and seven groundwater nodes. In this study groundwater inflows are set at the licence abstraction limit, defined by the Environment Agency (Environment Agency, 2013b). The scenarios of flow and demand are input into the model and a minimum cost flow problem is solved at every time-step, t,

in the simulation. Each arc has a transfer cost; the higher the transfer cost the less likely the arc will be chosen to transport flow. Carryover arcs ensure flow is not wasted. The performance of solution s relative to the two objective functions is evaluated after all scenarios (X) have been simulated. The performance criteria inform the optimization module.

An εMOGA (Laumanns et al. 2002) solves the optimization problem, using the ε-dominance concept to identify non-dominated solutions in the objective space. The algorithm is set to binary, one-point crossover, with bitwise mutation to prevent converging to a local optimum and ensure the solutions identified are diverse and well distributed (Borgomeo et al. 2016; Mortazavi-Naeini et al. 2012; Mortazavi-Naeini et al. 2014). The probability of crossover is set to 1.00, diagonal swap in one-point crossover to 0.20, mutation to 0.05, and inversion to 0.05. The multi-objective optimization was performed on high performance computers with Intel cores; each run used 20 nodes with 16 individual cores.

4.3.2 Observable indicators

As established in **Section 4.2.2**, the observable indicators selected for Step 3 should be indicative of emerging trends in the water resource system (Haasnoot et al. 2018). River flow and water demand were identified in discussions with stakeholders in Thames Water and the Environment Agency as being most relevant to their adaptation planning in the London region. Nominated indicators included the number of days a flow statistic is less than the equivalent historical statistic, moving averages of a flow statistic, average population growth, and average demand. Ultimately, 5 different flow statistics (Q80, Q85, Q90, Q95 and Q98) with five distinct observation windows (1-, 5-, 10-, 20- and 30-year), and three demand measures (1-, 5-, and 10yr total annual demand) were shortlisted. Here,

a flow statistic of Q80 represents the value when flow is exceeded for 80% of the observation window. We also consider five reservoir statistics (1-, 5-, 10-, 20- and 30-year average simulated reservoir level), as reservoir levels respond directly to changes in river flow and demand. Finally, we include an indicator related to time (year in simulation) to account for non-stationarity in the observable indicators.

First, we quantify the expected risk of water shortages, h_t^i, in the London WRZ in a 'no adaptation' future. The expected risk is derived from the objective function $f(2)$, and is calculated for individual time-steps in simulations of the Thames Water supply system model under ensemble X. Because we are evaluating indicators with observation periods of up to 30 years, we focus on a simulation period of 50 years (out of a total 80 years). The risk metric represents the aggregate restriction cost over the remainder of the simulated time series beyond time-step t. The metric is calculated: $h_t^i = \sum_j^q (E_l)_j$, whereby $(E_l)_j$ denotes the estimated cost of a restriction of severity (level) l incurred at time-step j, where $j = t + 1$. Second, OLS regression models are built to fit the responses of h_t^i to different combinations of the candidate observable indicators. For simplicity, we fit models in the following order:

(i) With an intercept and one observable indicator;

(ii) With an intercept, one observable indicator, and the indicator for time;

(iii) With an intercept, two observable indicators, and the indicator for time.

To ensure parsimony in the monitoring system, we do not fit models with a reservoir indicator and a flow/or demand indicator. Models are eliminated if the *p-value* for coefficient estimates are greater than 0.05. If a flow, demand or reservoir indicator is not significant when we include the time indicator, the decision rules using that indicator are assumed to be no better than rules that use only time. Candidate indicators and/or

combinations of indicators are selected based on their ability to predict the risk metric, as indicated by a model's Ordinary R^2 value and RMSE.

4.3.3 Strategy generation and testing

WATHNET-5 is run under the 100 transient scenarios (X) at a daily time-step. The optimization process is conducted for each candidate indicator or combination of indicators. As the optimizer module runs it performs a comprehensive search for the best combination of option capacities and decision rule thresholds for the candidate indicators. The Pareto-optimal strategies generated in each search contain the rule-based strategies that determine if and when an option is implemented in the Thames Water system. The range of solutions illustrate the trade-off between adaptation cost (objective function $f(1)$) and expected restriction cost (objective function $f(2)$). In this step we also generate the Pareto-frontier of 'fixed' plans, which is used as the counterfactual to the rule-based strategies.

We calculate the hypervolume of each Pareto-frontier using the Hypervolume Computation script for Matlab by Johannes (2020). The upper bound reference point for the hypervolume calculation is set at the maximum objective function values achieved on the fixed plan frontier. This is to ensure the hypervolume estimations for the rule-based frontiers are comparable. For each frontier, the hypervolume script computes the Lebesgue measure of the objective function values by means of Monte Carlo approximation, with a sample size set at 100,000. We repeat the hypervolume script 100 times for each frontier. The final hypervolume estimates are calculated by averaging the hypervolume values from the 100 iterations.

4.4 Results

4.4.1 Indicator screening

This section presents results from the observable indicator screening conducted in Step 2 of the planning framework. **Table 4.2** presents the highest performing linear regression models from the screening; **Data Set S1** (see **Appendix A7**) presents the complete results from the indicator screening, with further details about model coefficients and *p-value*s. **Table 4.2** is divided into subsections corresponding to indicator type ('reservoir level', or 'demand and flow'), and by the window of observation for the flow statistics (1-, 5-, 10-, 20-, and 30-year).

Several conclusions can be drawn from the results. First, predictive ability increases when time is included as an indicator in the linear model. This is unsurprising as the linear model response variable (risk metric) is a calculation of the aggregate restriction cost over the remainder of the time series. The results strengthen the argument that using time as an indicator helps to avoid issues of non-stationarity in the other observable indicators. Second, 1-year annual demand outperforms demand indicators with a longer observation window. For this reason, we only present results from 3-term models that use a 1-year annual demand indicator. Third, predictive ability is highest for linear models that use a flow, demand, and time indicator. Models in this form outperform models that use average reservoir levels (models 1 to 5). The 3-term models exhibit similar ordinary R^2 scores, but more distinct RMSE scores. In all cases, the ranking of models by R^2 and RMSE scores remain the same. In general, the highest performing 3-term models contain extreme low flow statistics (Q95 and Q98). This suggests that the performance of the Thames supply system, as indicated by the prediction of restriction cost, is more sensitive to drought events. Finally, for the 3-term models using time, flow and 1-year annual demand, R^2 and RMSE improves as the window of observation for the flow statistic

increases from 1-, to 5-, to 10-, to 20-year periods. No improvement is observed between 20- and 30-year flow statistics.

The highest performing model uses a 20-year Q95 flow statistic, 1-year annual demand, and time (model 24). This combination of indicators is used in Step 3 to create decision rules of the form: IF *"20yrQ95 is less than threshold value 1"* AND *"1yrDem is greater than threshold value 2" AND "current year is greater than threshold value 3"* THEN *"build infrastructure option a with capacity c_a, with the option operating functionally after the lead time m_a has elapsed"* ELSE *"do nothing"*. For illustrative purposes, we choose two additional combinations of indicators to use in Step 3 (highlighted bold in **Table 4.2**). This choice is based on performance of the models in each subgroup defined by flow observation window. Models with 1-year observation windows (models 6 to 10) are excluded because one or more coefficients are not significant (*p-value* > 0.05). Models with 30-year windows (models 26-30) are excluded because they exhibit low observability (Raso et al. 2019) compared to the shorter 20-year flow indicators. Consequently, models 15 and 20 are selected as they are the highest ranked models within their subgroup.

Table 4.2. Highest performing linear regression models identified in indicator screening. Selected indicators taken into Step 3 are highlighted in **bold**.

Model number	Linear model	Selection Criteria		
		RMSE	Ordinary R^2	*p-value* <0.05
1	$h = \beta0 + 1yrRes + t + \varepsilon$	72530541573	0.1310	Yes
2	$h = \beta0 + 5yrRes + t + \varepsilon$	70556450593	0.1546	Yes
3	$h = \beta0 + 10yrRes + t + \varepsilon$	69116510028	0.1719	Yes
4	$h = \beta0 + 20yrRes + t + \varepsilon$	74275386571	0.1101	No
5	$h = \beta0 + 30yrRes + t + \varepsilon$	74268433461	0.1102	Yes
6	$h = \beta0 + 1yrQ80 + 1yrDem + t + \varepsilon$	61988747507	0.2573	No
7	$h = \beta0 + 1yrQ85 + 1yrDem + t + \varepsilon$	61988430566	0.2573	No
8	$h = \beta0 + 1yrQ90 + 1yrDem + t + \varepsilon$	61988247098	0.2573	No
9	$h = \beta0 + 1yrQ95 + 1yrDem + t + \varepsilon$	61988013391	0.2573	No
10	$h = \beta0 + 1yrQ98 + 1yrDem + t + \varepsilon$	61986389640	0.2573	No
11	$h = \beta0 + 5yrQ80 + 1yrDem + t + \varepsilon$	61987675934	0.2573	No
12	$h = \beta0 + 5yrQ85 + 1yrDem + t + \varepsilon$	61985257853	0.2574	No
13	$h = \beta0 + 5yrQ90 + 1yrDem + t + \varepsilon$	61982123942	0.2574	Yes
14	$h = \beta0 + 5yrQ95 + 1yrDem + t + \varepsilon$	61979104535	0.2574	Yes
15	$\boldsymbol{h = \beta0 + 5yrQ98 + 1yrDem + t + \varepsilon}$	**61976935965**	**0.2575**	**Yes**
16	$h = \beta0 + 10yrQ80 + 1yrDem + t + \varepsilon$	61986272623	0.2573	No
17	$h = \beta0 + 10yrQ85 + 1yrDem + t + \varepsilon$	61978945039	0.2574	Yes
18	$h = \beta0 + 10yrQ90 + 1yrDem + t + \varepsilon$	61968097793	0.2576	Yes
19	$h = \beta0 + 10yrQ95 + 1yrDem + t + \varepsilon$	61954856116	0.2577	Yes
20	$\boldsymbol{h = \beta0 + 10yrQ98 + 1yrDem + t + \varepsilon}$	**61948011005**	**0.2578**	**Yes**
21	$h = \beta0 + 20yrQ80 + 1yrDem + t + \varepsilon$	61986230870	0.2573	No
22	$h = \beta0 + 20yrQ85 + 1yrDem + t + \varepsilon$	61972294569	0.2575	Yes
23	$h = \beta0 + 20yrQ90 + 1yrDem + t + \varepsilon$	61937571714	0.2579	Yes
24	$\boldsymbol{h = \beta0 + 20yrQ95 + 1yrDem + t + \varepsilon}$	**61909044794**	**0.2583**	**Yes**
25	$h = \beta0 + 20yrQ98 + 1yrDem + t + \varepsilon$	61919698520	0.2581	Yes
26	$h = \beta0 + 30yrQ80 + 1yrDem + t + \varepsilon$	61988801917	0.2573	No
27	$h = \beta0 + 30yrQ85 + 1yrDem + t + \varepsilon$	61984752989	0.2574	No
28	$h = \beta0 + 30yrQ90 + 1yrDem + t + \varepsilon$	61959704711	0.2577	Yes
29	$h = \beta0 + 30yrQ95 + 1yrDem + t + \varepsilon$	61931290074	0.2580	Yes
30	$h = \beta0 + 30yrQ98 + 1yrDem + t + \varepsilon$	61939034113	0.2579	Yes

Key:

h - Risk metric
Dem - Annual demand
β0 - Intercept
t - Time
Res - Average reservoir level
ε - Error term
Q - Flow statistic
RMSE – Root Mean Squared Error

4.4.2 Strategy generation

This section presents the results from the four multi-objective searches conducted in Step 3 of the planning framework. **Figure 4.3** shows the Pareto-optimal solutions for each optimization run and illustrates their relative performance in the objective space. Each solution outlines a 60-year plan or rule-based strategy for a planning period from 2030 to the end of 2089. The fixed plans specify the year (elapsed time) in which an option is triggered; the rule-based strategies outline the time, flow, and demand conditions that must be exceeded for an option to be triggered. The three combinations of indicators identified in Step 2 (**Section 4.4.1**) are herein referred to as Indicator Group A (model 15), Indicator Group B (model 20), and Indicator Group C (model 24).

In all four sets of solutions, the most expensive rule-based strategies and fixed plans contain multiple options, each with conditions that trigger early option implementation. The least expensive solutions avoid costly options and delay system modification until later in the planning period. These low-cost solutions result in a high frequency of severe restrictions. Moreover, all of the fixed plans and rule-based strategies presented in **Figure 4.3** choose the 'reduced' demand management policy, which is the cheapest of the four available. The most frequently selected options (as identified by a positive option capacity) in the fixed plans and rule-based strategies are broadly similar, with over 77% of solutions in each search selecting Option 1, and over 99% picking Option 2. Option 3 is selected in 22% of fixed plans, and 28% and 29% of strategies with indicator Group A and B, respectively. Only 4% of strategies with indicator Group C assign a positive capacity for Option 3. Option 4 is rarely chosen in the fixed plans, or in strategies with Groups A and B indicators (<7%), but is selected in 28.4% of strategies in Group C. Finally, Option 5 is more popular in the rule-based strategies (>42%) than fixed plans (33.6%).

Figure 4.3 indicates that rule-based strategies are most likely to outperform fixed plans in areas of the objective space where expected total costs are between £2.3M $x10^2$ and £2.8M $x10^2$, and expected restriction costs are between £2.5M $x10^4$ and £12.5M $x10^4$. In this region the average decrease in expected total cost, relative to fixed plans with an equivalent restriction cost, is 0.91% in Group A strategies, 0.86% in Group B, and 1.35% in Group C. In the same region, the average decrease in expected restriction cost, relative to fixed plans with an equivalent expected total cost, is 8.33% in Group A, 8.04% in Group B, and 13.1% in Group C. The flexible solutions perform better on average than their fixed counterparts because options are only included in the system when the observational trends in demand and flow indicate so, and therefore the costs associated with construction and infrastructure operation occur only in years when the options are needed and not sooner (Steinschneider & Brown, 2012). The inclusion of a time indicator in the rule-based strategy search also helps to avoid options being implemented as a result of random shocks to the system which do not necessarily represent the long-term trends emerging from the climate and demand conditions. For example, a rare extreme event at the beginning of a scenario may satisfy the conditions required to trigger an option, but this option may not be needed for the remainder of the scenario if the long-term trend is milder than the early extreme event signposted. The time indicator therefore ensures that the options are not implemented earlier than is essential in each scenario. This effect is less important for an indicator with a long observation window, as the increased number of observations has a smoothing effect on the indicator trend. Further motivation for including a time indicator in the rule-based strategies arises from the underlying principle of a fixed plan. A rule-based strategy cannot recreate the exact outcome of an optimal fixed plan (under identical future scenarios) without the time indicator. For example, a fixed plan that stipulates an option being built in 2050 for all 100 future scenarios is only replicated in a rule-based

strategy with a high flow threshold, low demand threshold, and time threshold of 2050. In this case, the flow and demand rules are satisfied early in the simulation, but the option is not triggered until the time threshold is surpassed. In this format, the rule-based strategies can only equal or improve on the fixed plan performance. This explains the convergence of solutions in the tails of the Pareto-frontiers, along which the rule-based strategies reproduce the adaptation actions enacted in the fixed plans. Overall, the results indicate that this approach is most appropriate for agencies with a balanced preference over the planning objectives. Agencies who value one objective over another may not benefit from the rule-based strategies, as the solutions in the tails of the Pareto curves offer no improvement on their fixed counterparts.

Figure 4.3 lists the estimated difference in hypervolume of the rule-based strategy Pareto-frontiers, relative to the frontier of fixed plans. The results reveal that indicator Group C (time, 20-year Q95, 1-year annual demand) produce the greatest improvement in objective performance. This is consistent with the results presented in Step 2 (**Section 4.4.1**), which indicate that this combination of indicators were the best predictors of future risk. For this reason, we select strategies using indicators from Group C for out-of-sample testing in Step 4. **Data Set S2** and **S3** (see **Appendix A7**) present the full set of pareto-optimal fixed plans and Group C strategies from the optimization experiment. The remainder of this section describes features of the strategies in Group C.

Type of planning portfolio	Symbol	Indicator Group	Indicator 1	Indicator 2	Indicator 3	Change in hypervolume (%)
Fixed plan		-	Elapsed time	-	-	0
Rule based strategy		A	Elapsed time	5 year Q98	1 year annual demand	0.72
Rule based strategy		B	Elapsed time	10 year Q98	1 year annual demand	0.73
Rule based strategy		C	Elapsed time	20 year Q95	1 year annual demand	1.01

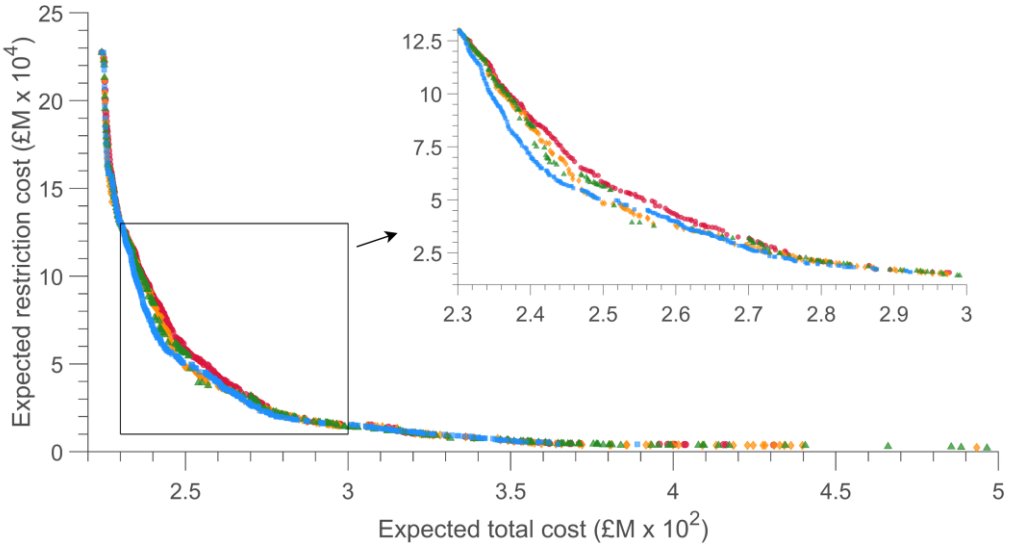


Figure 4.3. Multi-objective optimization output. Each frontier corresponds to the different combinations of indicators used in the search.

Figure 4.4 illustrates the decision space occupied by options in all strategies from Group C. Each box in plots **a** to **e** represent the decision rules specific to an option with a capacity greater than zero, with the box boundaries defined by the thresholds for the flow and demand indicators. The level of shading in each plot indicates the frequency with which the option features in the rule-based strategies. The size of the box signposts the likelihood of option implementation. A large box represents a decision rule with low thresholds over which an observable indicator must surpass to trigger an option. A smaller box represents a decision rule with more severe thresholds. Plot **f** depicts the distribution of thresholds for the time indicator for Options 1 to 5 in the rule-based strategies. Options with early time thresholds have darker shaded boxes in the left of the plot, whilst options with later time

thresholds have darker boxes to the right. The figure indicates that Option 1 and 5 have the widest range of time thresholds, whilst Option 4 has the narrowest range. The early thresholds for Option 4 are attributed to the long construction lead time for the reservoir, which delay the earliest time in which the reservoir capacity is available to the water user.

Together, the plots in **Figure 4.4** indicate that Option 2 is the most likely option to be triggered in the Group C strategies, followed by Options 1 and 5. Options 2 and 5 are likely to be triggered early in the simulation, whilst Option 1 is more likely to be triggered later. Options 3 and 4 are least likely to be triggered, requiring observations of severe low flow events and/or high annual demand.

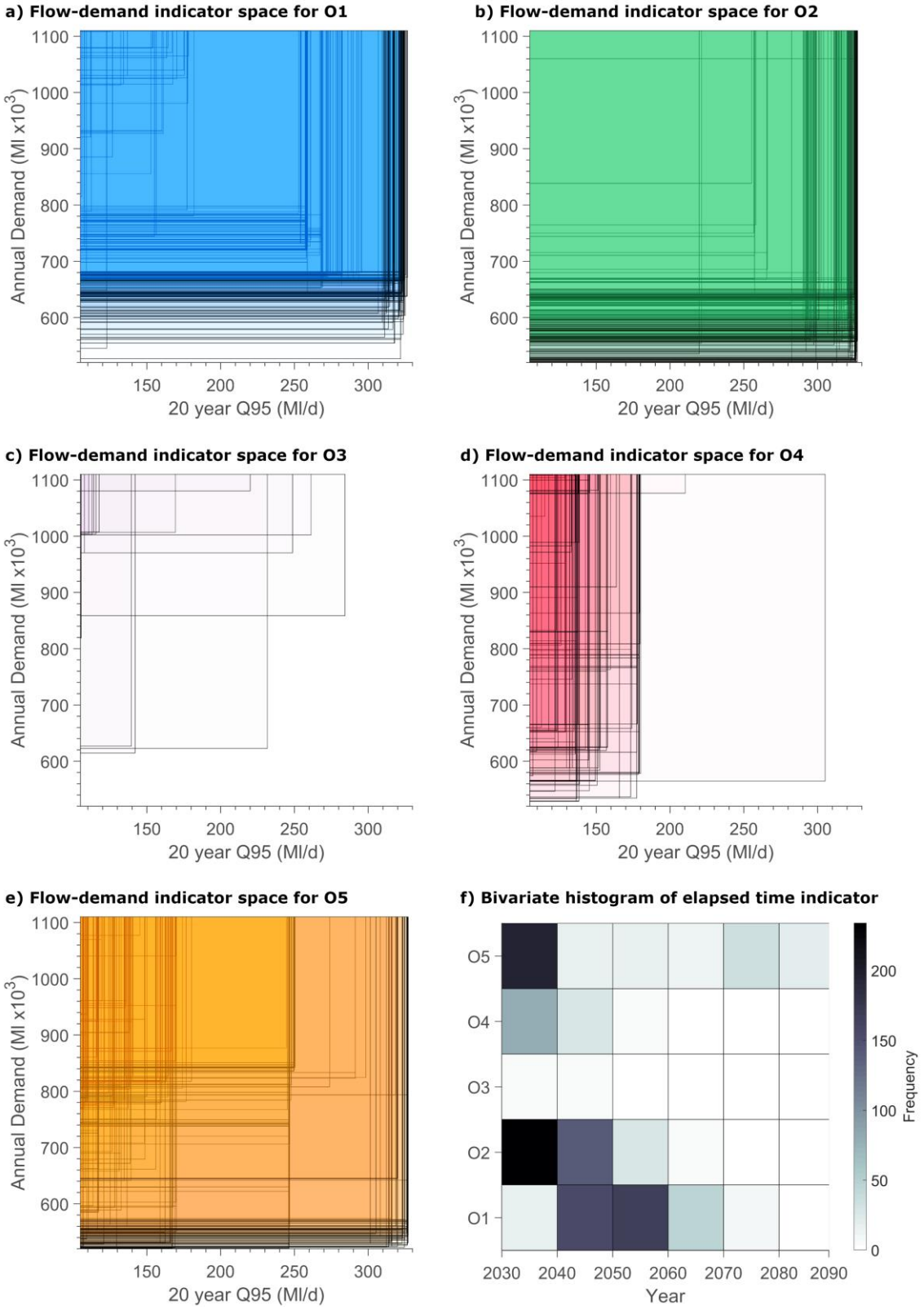


Figure 4.4. Option space defined by flow and demand indicators of optimal rule-based strategies using indicator Group C (**a** to **e**) and bivariate histogram of the time indicator (**f**) for all options with a capacity greater than zero Ml/d.

4.4.3 Strategy testing

A selection of rule-based strategies from Step 3 are resimulated against the new scenarios of randomly paired flow and demand time series in ensemble X^*. This out-of-sample simulation allows comparison of strategy performance under future scenarios not yet tested against. The rule-based strategies selected for resimulation are marked S1 to S4 in **Figure 4.5** and described in **Table 4.3**. The objective performance of the resimulated solutions is represented by the dark blue diamonds in **Figure 4.5a**. **Figure 4.5b** to **e** present the empirical cumulative distribution of estimated total costs and restriction costs across the scenarios in ensemble X and X^*.

Each resimulated solution experiences a shift in objective performance. Small changes are observed in expected total cost, with the largest average increase in expected cost from the resimulated strategies observed under S2 (+0.4%). Larger differences emerge between the estimations of expected restriction cost, with average increases of +5.2%, +5.3%, +4.0%, and +13% under strategies S1, S2, S3, and S4, respectively. Variance in total cost increases from left to right along the frontier, whilst variance in restriction cost decreases. The high variance in capital and operating expenditure from the rightmost strategies is attributed to more variable option implementation across the ensembles. The same pattern in variance exists along the frontier of fixed plans presented in **Figure 4.3**. In fixed plans, however, variance in total cost is driven solely by differences in operating expenditures between scenarios, rather than capital expenditure. This is because fixed plans implement an option in the same year of each simulation, regardless of the conditions observed.

In spite of the small differences in performance, all four resimulated rule-based strategies perform better than the original fixed plan frontier. The out-of-sample simulation suggests that: (i) the selected strategies are not over-fit to the scenarios in ensemble X used

in the optimization search, and; (ii) the rule-based strategies out-perform the fixed plans across a wide range of future uncertainties.

Table 4.3. Group C Strategies selected for out-of-sample testing. Decision rules are excluded if option capacity is zero.

S1	**Build O1 (300Ml/d) IF:** t > 2063 **&** 20yrQ95 < 259 **&** 1yrDem > 738378	**Build O2 (300Ml/d) IF:** t > 2047 **&** 20yrQ95 < 292 **&** 1yrDem > 634180	**Demand Policy 1**	-
S2	**Build O1 (600Ml/d) IF:** t > 2057 **&** 20yrQ95 < 268 **&** 1yrDem > 752493	**Build O2 (300Ml/d) IF:** t > 2046 **&** 20yrQ95 < 321 **&** 1yrDem > 623729	**Build O5 (150Ml/d) IF:** t > 2082 **&** 20yrQ95 < 170 **&** 1yrDem > 853891	**Demand Policy 1**
S3	**Build O1 (600Ml/d) IF:** t > 2057 **&** 20yrQ95 < 282 **&** 1yrDem > 658153	**Build O2 (300Ml/d) IF:** t > 2030 **&** 20yrQ95 < 325 **&** 1yrDem > 557412	**Build O3 (150Ml/d) IF:** t > 2084 **&** 20yrQ95 < 284 **&** 1yrDem > 858723	**Demand Policy 1**
S4	**Build O1 (600Ml/d) IF:** t > 2048 **&** 20yrQ95 < 326 **&** 1yrDem > 637826	**Build O2 (300Ml/d) IF:** t > 2030 **&** 20yrQ95 < 326 **&** 1yrDem > 556764	**Demand Policy 1**	-

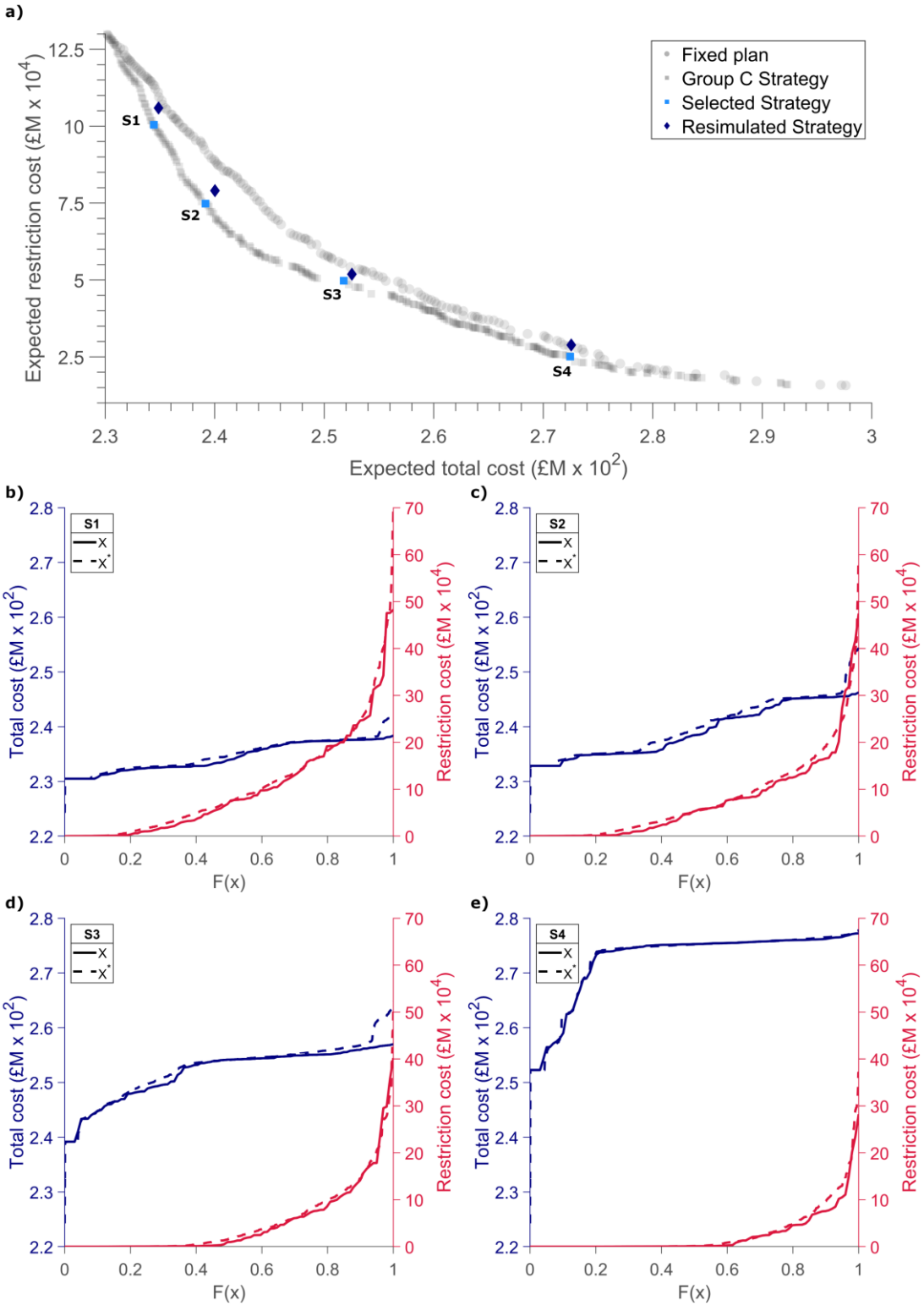


Figure 4.5. Performance of resimulated strategies. **Figure a** plots the expected total cost and expected restriction costs for resimulated rule-based strategies (S1 to S4). **Figures b** to **e** plot the empirical cumulative distribution of total cost and restriction cost from strategies S1 to S4 when simulated against ensemble X and X^*.

Figure 4.6 illustrates the frequency and timing of option implementation of rule-based strategy S3 (**Figure b**), fixed plan F1 (**Figure c**), and fixed plan F2 (**Figure d**) when resimulated against the 1000 new scenarios in ensemble X^*. Fixed plans F1 and F2, as identified in **Figure 4.6a**, are chosen for their comparability in objective performance to strategy S3 when simulated against the original scenarios in ensemble X. All three solutions feature rules that trigger Option 1 with capacity 600Ml/d and Option 2 with capacity 300Ml/d. Plans F1 and F2 implement Option 1 in 2063 and 2062, and Option 2 in 2031 and 2039, respectively.

The crosses in **Figure 4.6b**, **c**, and **d** represent the observable conditions (20-year Q95 and annual demand) when an option is implemented in each scenario. The coloured boxes represent the decision boundaries (thresholds) of the flow and demand decision rules in strategy S3. **Figure 4.6b** indicates that under strategy S3, Option 2 is likely to be implemented early in the simulation, whilst Option 1 and 3 will be triggered later. The plot demonstrates when and in how many scenarios an option in S3 is triggered, and how effectively the decision space within the box is utilised under the future scenarios in X^*. Note that in **Figures c** and **d** the options are implemented in every scenario, regardless of conditions observed. Strategy S3, by contrast, ensures that the options are only triggered (i) as future uncertainties are realised and (ii) when they are actually needed. The distribution of crosses in the plots of F1 and F2 show how options from the fixed plans can be unnecessarily introduced to the system when the stresses from flow and demand are relatively low. For instance, Option 2 is implemented in several scenarios under F1 and F2 when annual demand is less than 560000Ml. In spite of this early adaptation, both resimulated fixed plans produce a higher expected restriction cost (£5.3×10^4 and £5.8×10^4, respectively) in the out-of-sample simulation compared to the resimulated strategy S3

(£5.2x10^4). This is despite plan F1 exhibiting a similar expected restriction cost to S3 in the original simulation under ensemble X. Overall, the resimulation experiment suggests that the fixed plans offer a higher risk of water use of restrictions than the equivalent rule-based strategy, and may incur unnecessary financial costs when the need for adaptation is low.

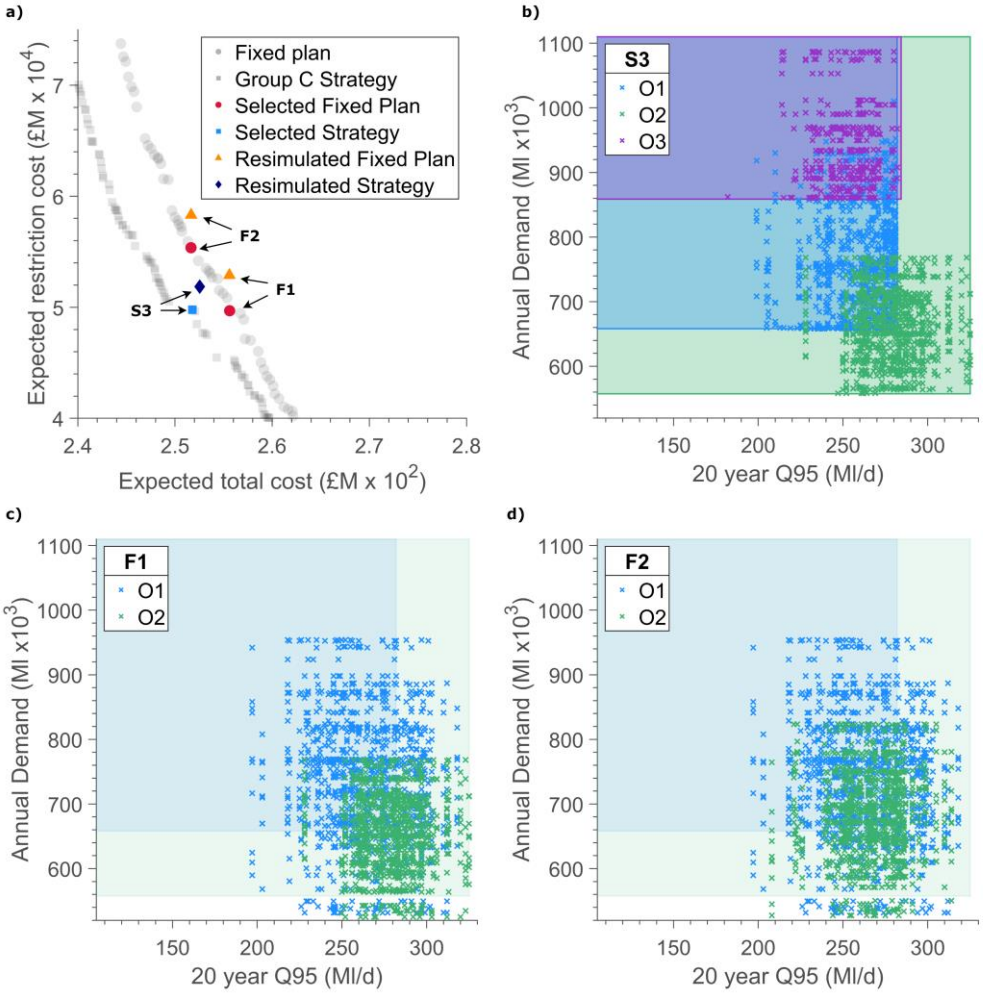


Figure 4.6. Illustration of option implementation in fixed plans F1 and F2 and rule-based strategy S3 when simulated against ensemble X^*. **Figure a** highlight the selected fixed plans and rule-based strategy on the original Pareto-frontiers. The crosses in **Figures b** to **d** represent the observable conditions (20-year Q95 and annual demand) when an option is implemented in simulation of each scenario in ensemble X^*. The boxes represent the option space defined by the flow and demand thresholds in strategy S3.

4.5 Conclusions

The benefits of flexibility in water resources planning have long been recognised (Fletcher, et al. 2019), but water resources planners have lacked practical tools to interpret system changes and implement adaptive strategies. In this paper we have proposed and demonstrated a pragmatic approach in which strategies are articulated in terms of a set of options, a set of indicators that need to be monitored, and decision rules that implement the options conditionally upon observations of the indicators. Within our decision rule framework, infrastructure options are triggered only when the observable indicators detect emerging trends in the water system (Raso et al. 2019; Robinson & Herman, 2019). The objective functions selected for the multi-objective optimization allow the water planner to trade-off the performance of strategies that are comprised of supply-side and demand-side options, with the total discounted cost of implementation. Performance is measured in terms of observable outcome variables of relevance to decision makers and water users: the frequency, severity and duration of water shortages, and the associated economic costs based on estimates of willingness to pay to avoid shortages. Visualisation of performance with respect to multiple objectives aids the evaluation of the optimal strategies when simulated against an extensive library of future flow and demand scenarios (Kasprzyk et al. 2013). Given the decision maker's tolerance to risk, economic budget and minimum performance requirements (Borgomeo et al. 2018; Stakhiv, 2011), they can select the most appropriate strategy and corresponding decision rules for their water system.

The observable indicators and decision rule thresholds are selected quantitatively, through regression analysis, simulation, and multi-objective optimization. This is more rigorous than previous research where choice of adaptation indicators and triggers are judgement-based and informed by stakeholder dialogue (Haasnoot et al. 2013; Zeff et al. 2016). Nonetheless, stakeholder engagement is central to our proposed management

process, informing the goals of system operation and navigating trade-offs between those goals. However, the choice of the best indicators should not be a matter of stakeholder judgement – it is a technical question given the overall goals and the properties of a system's observable behaviour (Herman et al. 2020).

To avoid the intractable computational expense of 'brute force' indicator optimization under uncertainty we have proposed a two-step approach, which first screens possible indicators according to their relevance to system performance, in order to obtain a parsimonious sub-set of possible indicators. In the second stage, indicators are chosen by selecting those that yield Pareto-optimal system performance when incorporated in a rule-based strategy. Unlike previous studies that use one indicator of change (Kirsch et al. 2013; Steinschneider & Brown, 2012; Zeff et al. 2016), this study monitors and responds to multiple indicators, so the adaptive strategy is therefore tailored to different drivers of change.

In the application to the Thames Basin in England, it was found that statistics of low river flows and water demand, as well as time, represented the most informative set of indicators. The Thames case study illustrates the benefits of this approach, when compared with fixed plans that were optimized by their performance on average over the whole ensemble. These fixed plans have high potential for regret in scenarios in which they impose an unjustified financial burden by investing in new supply capacity in futures where the increase in demand or reduction of supply is less than anticipated. Implementing a fixed plan instead of a rule-based strategy requires the water planner to commit to long-term large infrastructure projects without knowing exactly how future conditions may evolve.

In the example presented here, the rule-based strategies in a key region of the objective space reduce expected capital and operating cost on average by 1.35% for a given

level of restriction risk, and reduce expected restriction cost on average by 13.1% for a given intervention cost. Out-of-sample resimulation demonstrated how rule-based strategies also perform notably better under unforeseen conditions. Results showed that expected restrictions costs under resimulated fixed plans were up to 12.4% more than the expected restriction costs of the comparative resimulated strategy. Whilst we do not explicitly include robustness as a planning objective in this framework, we believe that the decision rules may be considered to be robust in that: (i) they have been optimized under a very wide range of possible future conditions, with a focus upon extremely undesirable performance (i.e. the most severe water shortages); and, (ii) they have been further tested in unforeseen conditions not used in the optimization and have proved to perform acceptably well and better than the baseline alternative.

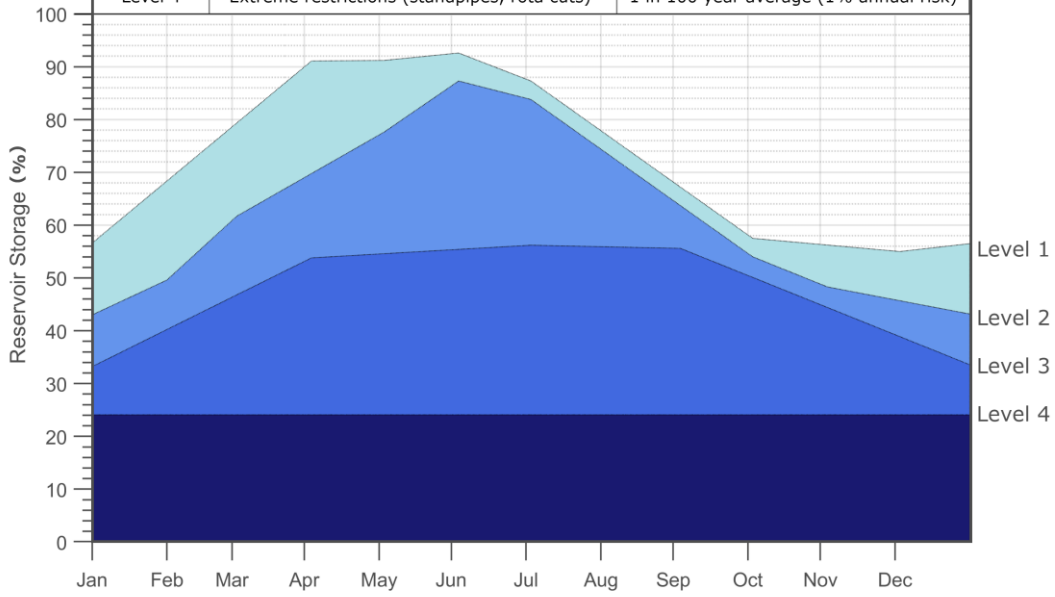
Though we believe the proposed approach represents a significant step both in rigour (for the reasons outlined above) and practicality (because decision rules are inherently intuitive), we recognise that there are still limitations in our method that require further research and development, besides dealing with the computational expense. The objective of preserving and enhancing the environment, which is central to sustainable water resources management, has been implemented as a constraint on the abstraction rules governing surface water withdrawals. Though it is unlikely that there would be any willingness to relax this constraint, water resources managers should be looking for ways to enhance the aquatic environment and reduce the impact of water withdrawals, which should be included as a further objective in the optimization method, combined with more explicit environmental indicators (Murgatroyd & Hall, 2021; Poff et al. 2016). Furthermore, this analysis deals only with water quantity, yet water quality is crucial for the aquatic environment and for the reliability of potable water supplies. Mortazavi-Naeini et al. (2019) examined trade-offs with river and reservoir water quality and quantity for

public water supplies in the Thames Basin, but using their coupled water quality modelling system within the optimization framework presented here may be computationally intractable. Moreover, roughly a fifth of water supply in the Thames Basin is withdrawn from groundwater sources, which interact with surface flows and are sensitive to climatic conditions, so a complete analysis would better account for groundwater and its system interactions. Finally, limitations on new water sources in the Thames Basin mean that large inter-basin transfers may be necessary to improve water system resilience to 21st Century drought events (Murgatroyd & Hall, 2020). To account for this, future work should extend the number of objectives and observable indicators presented in this planning framework to also include those that are germane to neighbouring basins. Though the complete system for adaptive management of water resource systems to achieve sustainability in challenging future conditions has yet to be fully integrated, we believe that the significant building blocks are now in place.

4.6 Appendix A: Supplementary materials to Chapter 4

4.6.1 Appendix A1

Severity of restriction	Measures for domestic customers	Expected frequency of occurrence
Level 1	Intensive water saving media campaign	1 in 5 year average (20% annual risk)
Level 2	Partial hosepipe ban and media campaign	1 in 10 year average (10% annual risk)
Level 3	Temporary use ban and non-essential use ban	1 in 20 year average (5% annual risk)
Level 4	Extreme restrictions (standpipes, rota cuts)	1 in 100 year average (1% annual risk)



Supplementary Figure 4.1. Lower Thames Control Diagram displaying the four levels of water restrictions, their corresponding interventions, and how they vary throughout the year [plotted using data from Thames Water (2014) and Thames Water (2019)].

4.6.2 Appendix A2

Steps to formulate transient scenarios using DECIPHeR flow scenarios.

4.6.2.1 Definitions

a_t^i is a flow value to be observed on day t, in Near Future scenario i.

b_t^j is a flow value to be observed on day t, in Far Future scenario j.

$g^i = \{a_1^i, \dots, a_n^i\}$ and $e^j = \{b_1^j, \dots, b_n^j\}$ represent individual scenarios, where $n = 10950$.

$NF = \{g^1, \dots, g^{100}\}$ and $FF = \{e^1, \dots, e^{100}\}$ represent the ensemble of scenarios.

4.6.2.2 Method

To calculate a transient scenario:

1. Identify Middle Future time series $f^k = \{a_1^r, \dots, a_s^r\}$, where r denotes one randomly selected scenario within the NF ensemble, and s is the number of days missing between the end of g^i and start of e^j. Here $s = 7300$.
2. Stitch together g^i, f^k and e^j to make new scenario c, where $c^l = \{a_1^i, \dots, a_n^i, f_1^r, \dots, f_s^r, b_1^j, \dots, b_n^j\}$. The new scenario is denoted by $c^l = \{o_1^l, \dots, o_{n^*}^l\}$, where n^* represents the end of the scenario. Here $n^* = 29200$. $o_{t^*}^l$ represents the new flow value to be observed on day t^*, in scenario l.
3. Calculate the mean and standard deviation of g^i and e^j, where:
    - $g_\mu^i = \frac{\sum_{t=1}^{n} a^i}{n}$
    - $e_\mu^j = \frac{\sum_{t=1}^{n} b^j}{n}$
    - $g_\sigma^i = \sqrt{\frac{\sum(a_t^i - g_\mu^i)}{n}}$
    - $e_\sigma^j = \sqrt{\frac{\sum(b_t^j - e_\mu^j)}{n}}$

4. Identify the location of the middle point of g^i and e^j within the new scenario o^l:
    - $p^l = \frac{n}{2}$. Here $p^l = 5475$.
    - $m^l = n^* - p^l$. Here $m^l = 23725$.
5. Identify the value at the middle point of g^i within the new scenario o^l:
    - $q^l = o^l_{p^l}$
6. Calculate μ_+ and σ_+.
    - $\mu_+ = \frac{e^j_\mu - g^i_\mu}{m^l - p^l}$
    - $\sigma_+ = \frac{e^j_\sigma - g^i_\sigma}{m^l - p^l}$
7. Using μ_+ calculate a scalar time series of the mean v^l, where $v^l = \{v^l_1, \dots, v^l_{n^*}\}$.
    - If $t^* < p^l, v^l_{t^*} = g^i_\mu - [(q^l - t^*) \times \mu_+]$
    - If $t^* > p^l, v^l_{t^*} = g^i_\mu + [(t^* - q^l) \times \mu_+]$
    - If $t^* = p^l, v^l_{t^*} = g^i_\mu$
8. Using v^l, calculate $\Delta v^l_{t^*}$, the difference between $o^l_{t^*}$ and $v^l_{t^*}$, where $\Delta v^l_{t^*} = \{\Delta v^l_{t^*}, \dots, \Delta v^l_{n^*}\}$.
9. Using σ_+ calculate a scalar time series of the standard deviation ρ^l, where $\rho^l = \{\rho^l_1, \dots, \rho^l_{n^*}\}$.
    - If $t^* < p^l, \rho^l_{t^*} = g^i_\sigma - [(p^l - t^*) \times \sigma_+]$
    - If $t^* > p^l, \rho^l_{t^*} = g^i_\sigma + [(t^* - p^l) \times \sigma_+]$
    - If $t^* = p^l, \rho^l_{t^*} = g^i_\sigma$
10. Calculate the transient flow at time t^* when $t^* \leq p^l$ using:
    - $x_{t^*} = (o^l_{t^*} + \Delta v^l_{t^*}) \frac{\rho^l_{t^*}}{g^i_\sigma}$
11. We calculate the transient flow at time t^* when $t^* > p^l$ using:

- $x_{t^*} = \left(o_{t^*}^{l} + \Delta v_{t^*}^{l}\right) \frac{\rho_{t^*}^{l}}{e_{\sigma}^{j}}$

12. $x_{t^*}^{l}$is the new flow value to be observed on day t^*, in transient scenario l.

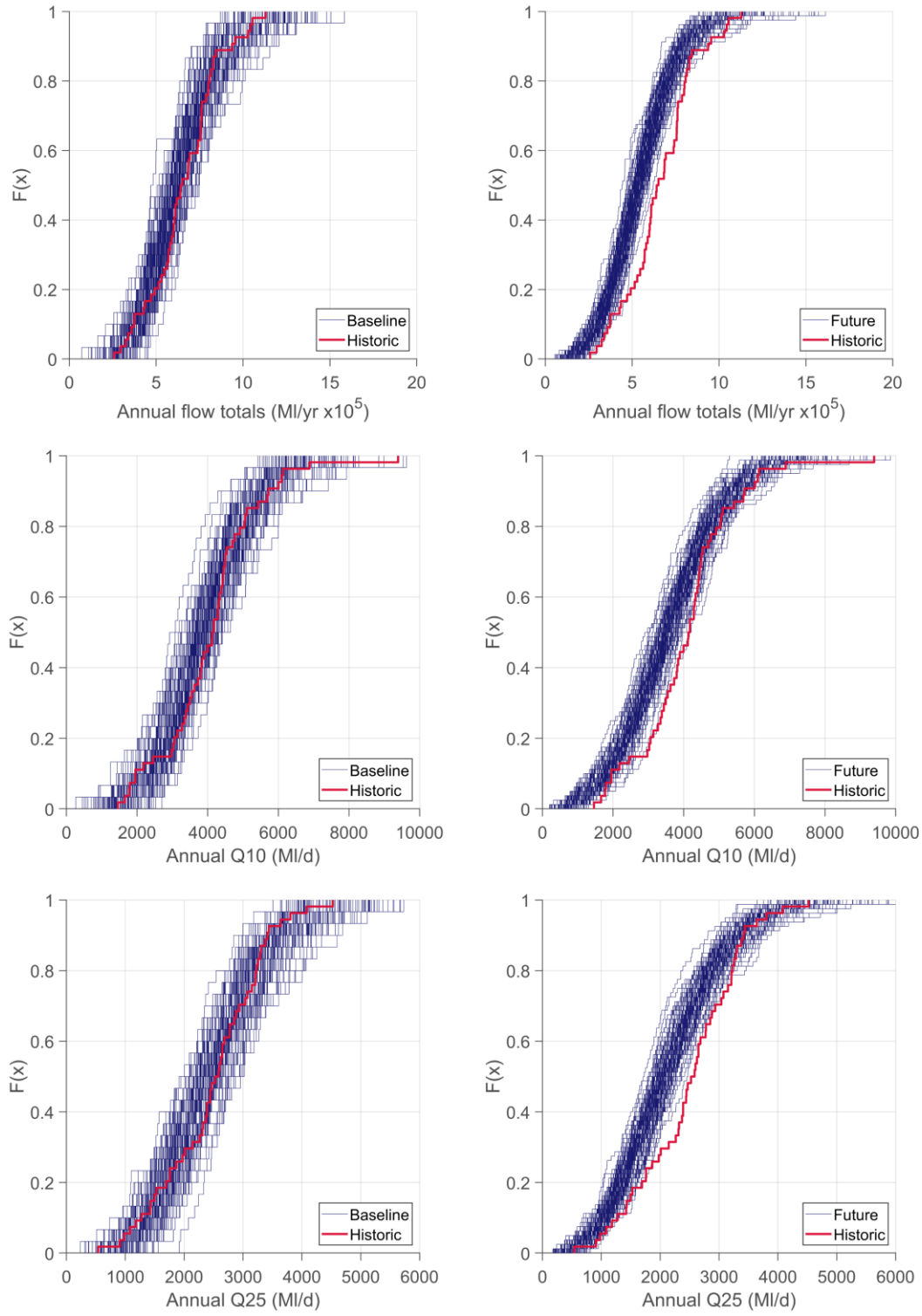
13. $z^l = \{x_1^l, \ldots, x_{n^*}^l\}$ represent individual transient scenarios, where $n^* = 29200$.

4.6.3 Appendix A3

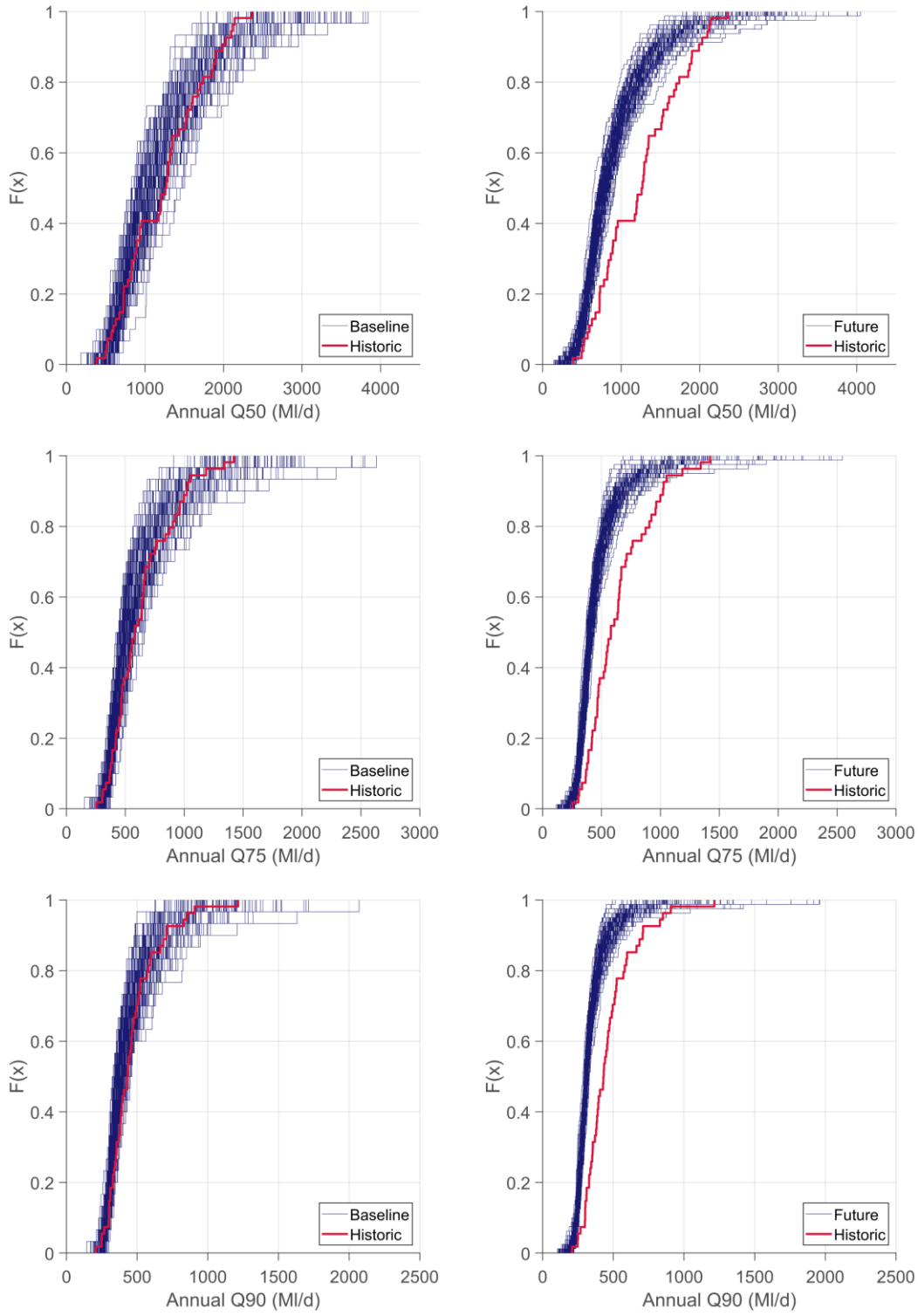
Supplementary Figure 4.2 and **Supplementary Figure 4.3** present Empirical cdf plots of simulated flows and flow statistics from the DECIPHeR modelling framework (Coxon et al. 2019) for the Upper Thames catchment (NRFA station 39008) when run using historically observed and RCP-driven precipitation (P) and evapotranspiration (PET) time series from the CEH GEAR (Tanguy et al. 2019) and Weather@Home (W@H) platform (Guillod et al. 2017), respectively.

Simulated time periods:

- Historic (1962-2015) – 1 realisation, generated using historic daily observed P (Tanguy et al. 2019) and PET (Robinson et al. 2016).
- Baseline (1975-2004) – 100 realisations, generated using different initial atmospheric conditions, and historic SST and sea ice records from HadISST (Rayner et al. 2003; Titchner & Rayner, 2014).
- Future (2010-2089) – 100 transient realisations, generated from projections of the original W@H Near Future and Far Future ensembles. The original ensembles were simulated using 50th percentile SST and sea ice projections (CMIP5, (Taylor et al. 2012)) under Representative Concentration Pathway (RCP) 8.5 (Meinshausen et al. 2011).

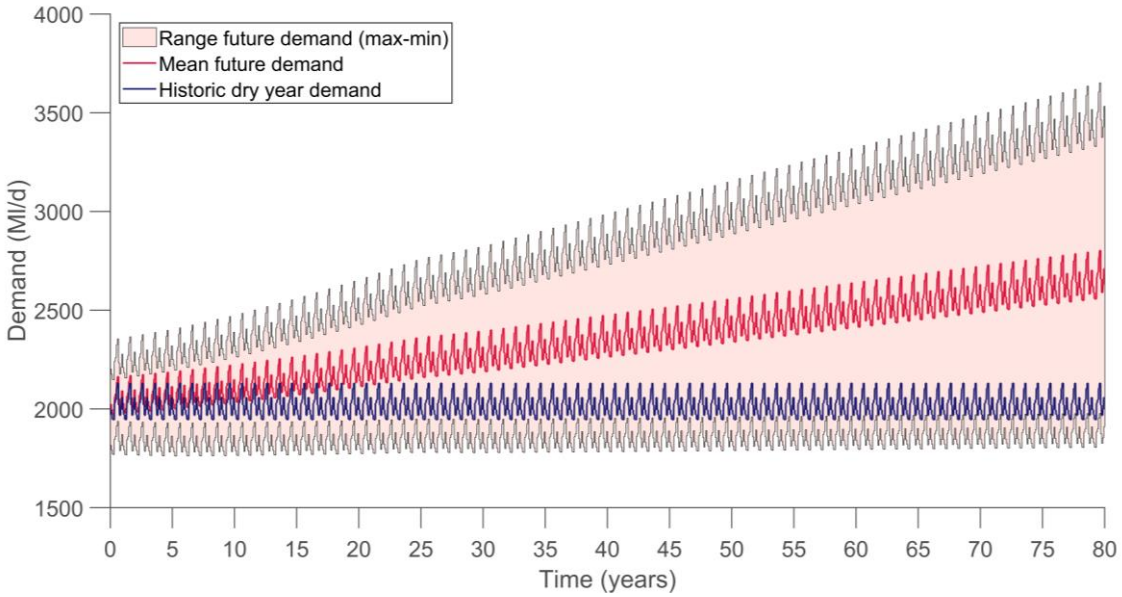


Supplementary Figure 4.2. Simulated annual flow totals, annual Q10, and annual Q25 for the Historic, Baseline, and Future periods.



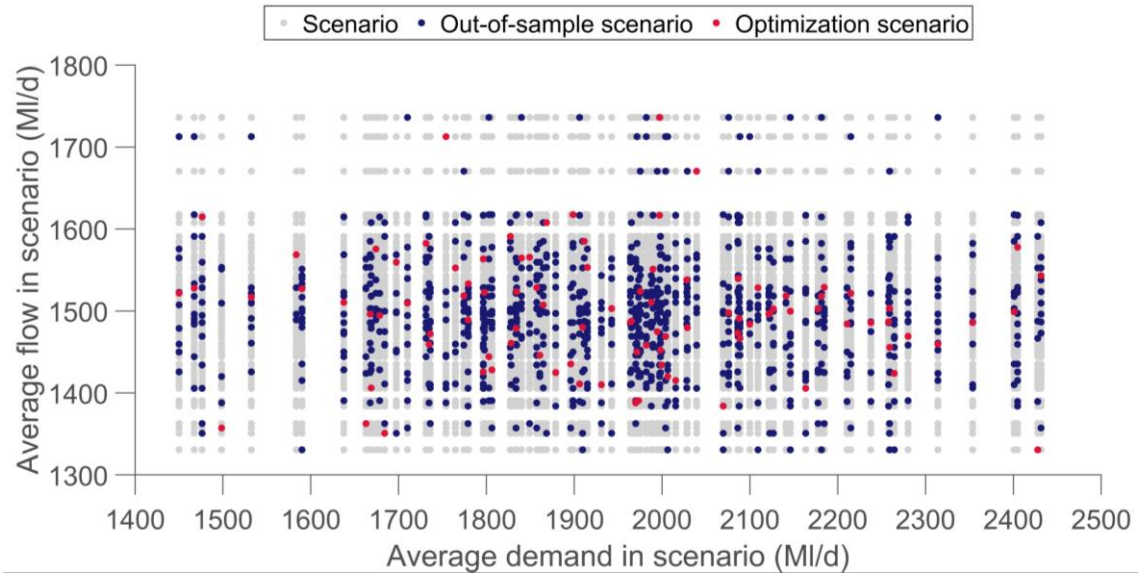
Supplementary Figure 4.3. Simulated annual Q50, annual Q75, and annual Q90 for the Historic, Baseline, and Future periods.

4.6.4 Appendix A4



Supplementary Figure 4.4. 80-year projected demand for the Thames Water London WRZ. Demand is given in mega-litres per day (ML/d). Intra-annual patterns of demand are a function of water resource zone monthly water demand profiles. Historical demand is estimated from Thames Water's 'dry year annual average distribution input' and monthly water demand profile.

4.6.5 Appendix A5



Supplementary Figure 4.5. Scatter plot of future ensembles. Each point denotes a scenario, which is created by randomly pairing one future flow projection and one future demand projection. An individual point represents the average demand in the London WRZ (Ml/d) and average future flow for the Upper Thames catchment inflow point (Ml/d; NRFA station 39008) projected in one scenario. A total of 10,000 possible scenarios exist. 100 (ensemble X) scenarios are used in Step 3 in the optimization search. 1,000 scenarios (ensemble X^*) are used in Step 4 in the out-of-sample strategy testing.

4.6.6 Appendix A6

Supplementary Table 4.1. Demand management policies. These policies aim to reduce distributional losses and public water demand.

Demand Management Policy	**Maximum estimated saving (Ml/d)**	**Max estimated OPEX (£M/y)**
Reduced	-60.3481	59
Maintain	-114.949	126
Min Effective	-122.987	141
Enhanced	-135.496	200

4.6.7 Appendix A7

Files uploaded as **Additional Materials**:

1. **Data Set S1 (dso1.xlsx).** Full results from the indicator screening in Step 2 of the planning framework.

2. **Data Set S2 (dso2.xlsx).** Complete set of fixed plans from multi-objective optimization, generated in Step 3 of the planning framework.

3. **Data Set S3 (dso3.xlsx)**. Complete set of rule-based plans using indicator group C from multi-objective optimization, generated in Step 3 of the planning framework.

5 The resilience of inter-basin transfers to severe droughts with changing spatial characteristics

Abstract

Faced with the prospect of climate change and growing demands for water, water resources managers are increasingly examining the potential for inter-basin water transfers to alleviate water shortages. However, water transfers are vulnerable to large-scale spatially coherent droughts which may lead to water shortages in neighbouring river basins at the same time. Under climate change, increasingly severe droughts are also expected to have greater spatial extent. We have integrated climate, hydrological and water resource modelling to explore the resilience of new transfer schemes between two neighbouring water companies in Southern England. An extended historical record of river flows and large ensemble of future flows derived from climate simulations were used to explore the effects of spatial and temporal drought variability. The analysis examines meteorological, hydrological and water resource drought events and how the spatial characteristics of these droughts may change with different transfer arrangements. Results indicate that all drought types examined are expected to increase in frequency and intensity throughout the 21st Century, but a new transfer has the capability to increase the resilience of water supplies. The analysis also highlights the importance of testing new water infrastructure against drought events that are more extreme and have different spatial patterns to those in historical records, demonstrating the value of scenario-based approaches to adaptive water resource planning.

5.1 Introduction

The changing climate and growth in water consumption poses new threats to water resource systems (Intergovernmental Panel on Climate Change, 2013), affecting the management of water resources (Ehsani et al. 2017) and increasing the risk of water shortages (Borgomeo et al. 2014). Notwithstanding large uncertainties in climate models, climate change is projected to alter the global hydrological cycle and transform the balance between evapotranspiration, runoff and precipitation (Liu et al. 2012). Precipitation trends and interannual variability have been shown to strongly control the water-balance (Ukkola & Prentice, 2013). Changes in precipitation patterns are therefore likely to impact the amount of water available for human use, with the potential to exacerbate droughts and associated water scarcity in water stressed areas throughout the 21st Century (Connell-Buck et al. 2011). Previous studies suggest that drought frequency and severity are important for water supply (Marsh et al. 2007), but that historical droughts provide a poor basis for future planning because the historical record is restricted to a handful of drought events with specific spatial and temporal characteristics (Watts et al. 2015). Feedbacks between water management operations and drought are also considered important for maintaining reliable water supplies (He et al. 2017), with studies revealing that human activities influence the probability of extreme hydrological drought (Van Loon et al. 2016), and manipulate the characteristics of drought along river networks (Tijdeman et al. 2018; van Oel et al. 2018; Wu et al. 2018). However, these studies are also limited to drought periods that exist in the historical record.

To ensure the resilience of water supply systems in an uncertain future, it is necessary to test the performance of water systems against a range of climatological, hydrological and socio-economic scenarios. This is particularly important for inter-basin water transfers, which rely on a reliable supply of water from one region to another. Inter-

basin transfers are defined as the ‘‘transfer of water from one geographically distinct river catchment, or basin to another, or from one river reach to another” (Davies et al. 1992), and have been widely used in an attempt to artificially improve water security in water scarce areas. In 2008, approximately 14% of global water withdrawals were transported via transfers; a statistic which is estimated to increase to 25% by 2025 (Gupta & van der Zaag, 2008). The design of water transfers can vary considerably depending on the needs of the importing and exporting regions, with the principal transfer types classified as permanent, short-term, temporary, reclaimed, water bank, or “wheeled” (Lund & Israel, 1995b). The focus of this study is on system capacity expansion through permanent inter-basin transfers, which are designed with the aim to (i) increase capability to meet demands, and (ii) improve long-term water system reliability.

Several efforts have been made to understand the value of inter-basin water management in alleviating water supply shortages during historical drought events. Cooperative transboundary management of water resources in the Blue Nile Basin has been shown to improve water security during drought events, but careful coordination is required to avoid harmful impacts to downstream water users (Wheeler et al. 2018). In the Western US, transfers have played an important role in managing water resources, with short-term emergency water transfers providing rapid response to emergency conditions during the 1991 and 1992 Californian droughts (Lund & Israel, 1995b), and cost-effective spot-market water transfers contributing to California’s pool of traditional water supplies (Lund & Israel, 1995a). At a continental scale, India’s National River Linking Plan aims to resolve national water scarcity issues by creating an interconnected water grid that transfers water between 37 rivers (Purvis & Dinar, 2020). The ambitious plan has received mixed reviews, with concerns raised regarding the geomorphological response to infrastructural changes and forced displacement of local communities (Gupta & van der

Zaag, 2008). As with other capacity expansion options, large scale transfers offer trade-offs between cost, revenue and reliability for the water managers (Zeff et al. 2014), with different inter-utility transfer agreement mechanisms offering risk reduction for both the water buyer and seller (Caldwell & Characklis, 2013; Lund & Israel, 1995b). Careful consideration of the impact of contractual transfer agreements on the environment is also key, with licensing agreements potentially benefiting consumers at the expense of increased risk to riverine habitats (O'Keeffe & De Moor, 1988; San-Martín et al. 2020; Wildlife and Countryside Link, 2016).

Permanent inter-basin water transfers incur costs and benefits, the balance of which differs for the water exporter and the water importer (Gupta & van der Zaag, 2008). As indicated above, these can include large financial costs incurred from construction and operation of transfer infrastructure, adverse ecological impacts, sustainability issues, and uncertain economic efficiencies afflicting existing transfer schemes (Purvis & Dinar, 2020). Whilst they are designed to improve security of supply, there are inevitable limits to the reliability of water transfers as well as potentially negative impacts. For this reason, water planners must test proposed transfer infrastructure and operating policies against a wide range of water supply, demand and socio-economic scenarios that contain conditions beyond what has been observed within historical records.

When designing transfer schemes, it is imperative that water planners understand the spatial coherence and intensity of drought events in neighbouring basins, ensuring that adaptation in one region does not lead to water shortages in another. This is important because transfers from a source location vulnerable to the same extreme drought events as the receiving location are more likely to fail than transfers between locations that have a low probability of coincident drought (Rahiz & New, 2012). For example, analysis of climatic-hydrological relationships in the headwaters of the Tagus River in central Spain

revealed that over-use of the Tagus-Segura Water Transfer in periods containing severe climatic droughts resulted in declined natural flow and lower reservoir levels in the transfer source region (Lorenzo-Lacruz et al. 2010). Further mismanagement of the transfer during critical periods affected economic activities in the transfer source region (Hernández-Mora & Del Moral, 2015), altered the downstream river environment through reduced hydraulic connectivity, and fuelled socio-political conflicts between the donor and recipient basins (San-Martín et al. 2020).

Previous work has examined the reliability of small treated transfers in the eastern United States against (i) historical observations (Palmer & Characklis, 2009) and (ii) stochastic streamflow data created using historical records (Kirsch et al. 2013; Zeff et al. 2016). For the purpose of exploratory modelling, artificial streamflow time series with increased frequency and intensity of droughts have also been used, generated by modifying streamflow generators (Herman et al. 2016). This research incorporates some aspects of potential future climates into transfer reliability assessments, relying on extreme events in the historical record to "stress test" adaptation options. More recent work examined the influence of within-basin raw water transfer (RWT) schemes on reliability and financial objectives when simulated against the future hydrologic conditions, with analysis revealing that RWT can reduce requirements for demand management interventions and inter-basin treated transfers, and contribute to lower regional financial risk (Gorelick et al. 2018). However, the eastern US-based studies do not fully account for spatial characteristics of drought types that may help to explain the ways in which transfers can prevent (or aggravate) water resource droughts during periods of extreme climate conditions and increased demand pressures. As Gorelick et al. (2018) hypothesise, the utility of raw water transfers are likely to depend on many features of the transfer regions, including available water storage, infrastructure, demand growth rates, and spatial

correlation of hydrologic events. Furthermore, the studies only investigate transfers that move small volumes (<100 Ml/d) of water, the conclusions of which may not be scalable to larger, inter-basin untreated water transfers. There is therefore considerable scope to investigate the operation of high-volume inter-basin transfers under future scenarios of change, and the impact these transfers have on water system performance in both exporting and importing regions.

The new large ensembles of climate model simulations used in this study, along with extended series of historical observations and demand growth scenarios, provide the opportunity to test the joint probability of coincident droughts more thoroughly than has hitherto been the case. We combine this with simulation modelling of the operation of water transfers, including a variety of strategies for how risks may be shared between neighbouring water utilities. This study aims to (i) explore the resilience of new high-volume inter-basin water transfer infrastructure with different operating agreements to severe meteorological and hydrological drought events, and; (ii) evaluate the level of risk and reliability of a given version of transfer infrastructure during drought events and water demand pressures not present in the historical record. The novel methodology proposed here demonstrates the importance of using large climate ensembles containing a wide range of climatological extremes in long term water resource planning, providing a mechanism to explore the joint occurrence of different types of drought events and associated consequences on transfer operation, cooperation and reliability.

The following analysis focuses on new unidirectional transfer infrastructure in South East England, connecting two private water companies, Severn Trent Water and Thames Water, who together supply more than 18 million people a year (Severn Trent Water, 2019; Thames Water, 2019a).

5.2 Study area, data and modelling framework

5.2.1 Study area

This study investigates the spatial characteristics of meteorological, hydrological and water resource drought in Southern England (**Figure 5.1**). Meteorological and hydrological drought are calculated for the Severn to Deerhurst and Thames to Kingston catchments and are consistent with the basins used in the UKCP09 climate projections (UKCP09, 2009) and the Severn Thames Transfer Study area (Rudd et al. 2018).

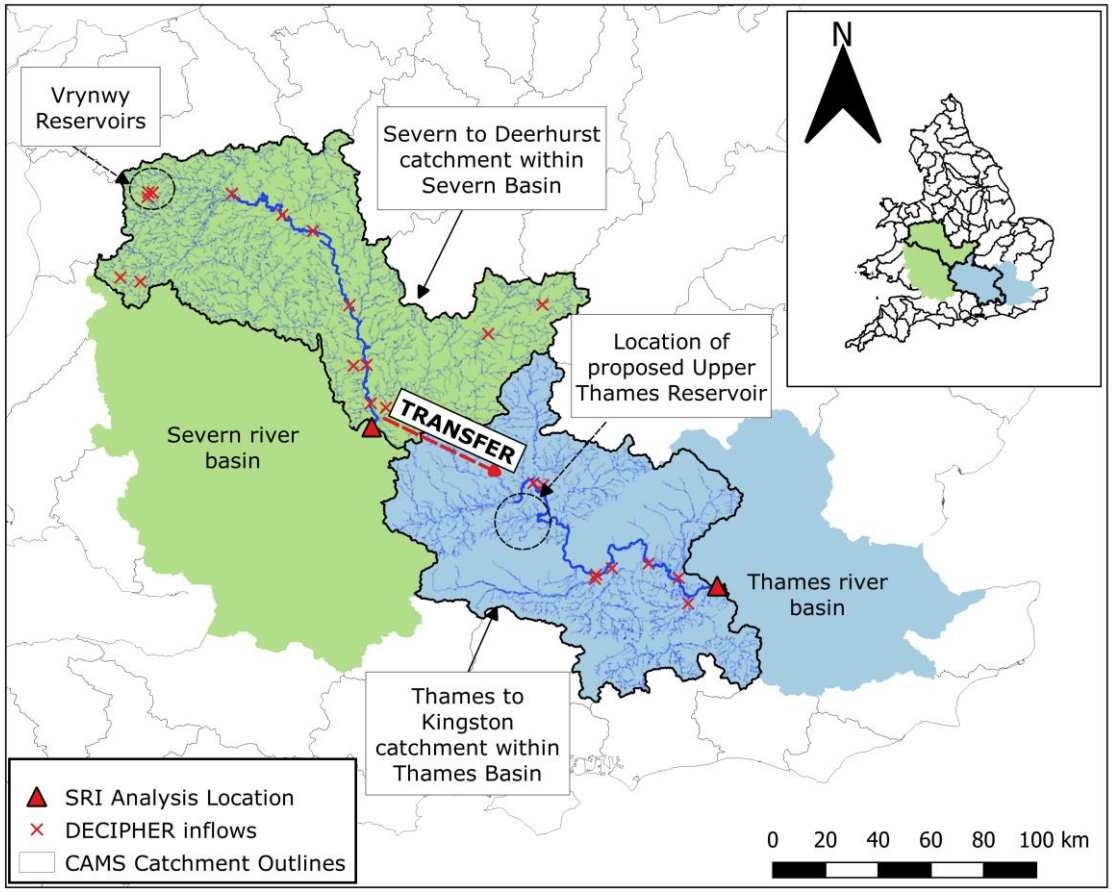


Figure 5.1. Study area.

Climate characteristics in Southern England vary between regions, with a gradient of precipitation from west to east caused by prevailing westerly weather systems (Fleig et al. 2011). This is reflected in observations of average annual precipitation, which was 724mm

in the Thames catchment to Kingston and 793mm in the Severn catchment to Deerhurst from 1961-1990 (NERC CEH Wallingford, 2018). Historical precipitation records reveal that meteorological droughts commonly occur in both the Severn and Thames Basins, but the impact of droughts vary depending on the duration, severity and management of the event (Vidal & Wade, 2009). In South East England, drought events are attributed to southerly weather fronts bringing warm air from continental Europe (Fleig et al. 2011). Droughts in the West can be explained by severe rainfall deficiencies (Marsh et al. 2007; Marsh, 2007) and circulation anomalies in the North Atlantic Oscillation (Rahiz & New, 2012).

Several studies have explored the spatial and temporal patterns of projected 21st Century meteorological droughts in the UK (Burke et al. 2010; Fowler et al. 2007; Rahiz & New, 2013; Vidal & Wade, 2009). Whilst estimations of future precipitation at regional scale are considerably uncertain (Hawkins & Sutton, 2011), general patterns of change can be inferred from ensembles of climate projections. For example, the UK Climate Projections 2009 (UKCP09; Murphy et al. 2009) ensemble estimate median decreases in summer precipitation in Southern England of -40% (confidence interval of -65% to 6%). Likewise, results from the Weather@Home modelling experiment by Guillod et al. (2018) reveal large decreases in summer precipitation across the UK for time periods in the middle and end of the 21st Century. Rahiz & New (2013) present an analysis of 21st Century droughts in the UK using monthly precipitation projections from the perturbed-physics ensemble, HadRM3-PPE-UK, to estimate a drought severity index. Results show an ensemble-mean increase in drought intensity, drought covariance and frequency of drought months for the Severn and Thames regions in the second half of the 21st Century. The findings support earlier work by Vidal & Wade (2009), Fowler et al. (2007) and Fowler & Kilsby (2004) who also report increased drought risk in South East England.

Overall, future projections suggest that by the end of the century droughts could be more spatially coherent, with large meteorological droughts in South East England affecting multiple catchments and threatening both existing and proposed water supply infrastructure.

Analysis of historical flow records reveal few changes in the pattern of hydrological drought and low flows in the UK in the 20th Century (Hannaford & Buys, 2012; Rudd et al. 2017; Watts et al. 2015). Streamflow records from the Severn and Thames Basins document historic hydrological drought events, with 15 major droughts in the Thames at Kingston and 17 in the Severn at Deerhurst between 1963 and 2015 (Rudd et al. 2018). These droughts varied in duration, severity and intensity, and had wide ranging impacts on the water sector. The 2004-2006 drought, for instance, impacted water supplies to over 13 million water consumers in South East England. Regional spring failures, low river flows, decreased stream connectivity and depleted groundwater levels resulted in increased stress in riverine environments and widespread implementation of drought mitigation measures. In the period between November 2004 and August 2006, total river flow in the Thames Basin fell to 56% of the long term average, while flows in the Severn dipped to only 74% of the long term average (Marsh et al. 2007). With careful management, water transferred from the Severn (or other less stressed areas) may have helped to alleviate environmental and demand pressures in the Thames Basin during this period.

Multiple methods exist to investigate future changes to streamflow and hydrological drought. For example, Hannaford et al. (2011) developed a 'drought from drought' forecasting methodology to identify streamflow droughts in Europe based on drought developing in neighbouring regions. Other studies have looked into the effects of climate change on groundwater resources in Southern England (Jackson et al. 2011),

evaluated the use of perturbed physics ensemble of climate models on water resource planning in South West England (Lopez et al. 2009), explored uncertain changes in low flows in the River Thames using statistical downscaling techniques and hydrological modelling (Wilby & Harris, 2006), and conducted multi-model assessments of water resources in the Thames catchment (Manning et al. 2009). A significant study of future changes to hydrology in Great Britain was conducted by Prudhomme et al. (2013), who developed a set of eleven transient daily river flow projections from 1951 to 2098 for 282 river sites using the HadRM3-PPE ensemble and a single hydrological model. Results indicate that spring and summer flows may decrease by -40 to -80% for most of the UK by the 2050s, whilst in autumn river flow may experience up to -80% decreases in the South and East of the country. Changes to mean annual flow were projected to be greatest in the West, with a reduction of up to -40%. However, the baseline simulations showed large deviations from observations in the pre-2000 reference period, due to climate modelling uncertainty and difficulties in validating naturalised flows in highly regulated systems, particularly during periods of low flow (Prudhomme et al. 2013). Moreover, eleven flow series were not a sufficiently large sample to robustly characterise the spatial statistical properties of extreme droughts. The more recent study by Rudd et al. (2019) uses ensembles of 21st Century emissions driven climate model data to investigate future changes in river flow and soil moisture droughts in catchments across Britain. Results from the threshold based approach indicate increased peak intensity, severity, duration and spatial extent of hydrological droughts in the South East by the end of the century, attributed to overall drying and increased potential evapotranspiration (Rudd et al. 2019).

Recent work has also projected increases in the frequency and intensity of coincident hydrological droughts – the likelihood of drought events occurring simultaneously in neighbouring basins (Rahiz & New, 2012) – in the Severn and Thames,

with the likelihood of droughts in the Thames affecting conditions in the Severn increasing into the future (Rudd et al. 2018). Correspondingly, the likelihood of non-coincident drought (when the Thames is in drought, but the Severn is not) is projected to decrease. The results emphasise the importance of evaluating future transfer infrastructure relying on water supply from the Severn to the Thames, as periods when the Thames is water stressed are more likely to coincide with periods when the Severn may not be able to spare water via the transfer scheme.

Management of water resources in the Severn and Thames regions are overseen by the privately-owned water companies, Severn Trent Water and Thames Water. Thames Water primarily supplies water from off-line raised reservoirs near population centres that are filled directly from the River Thames and from groundwater sources. Severn Trent's water supply is regulated by upstream on-line storage reservoirs. Operation of the reservoirs and river abstractions are regulated by operating agreements, as described in **Section 5.4.4**. The companies must report periodically to the economic and environmental regulators, OFWAT and the Environment Agency, respectively, submitting investment plans outlining how supply to water customers will be secured into the future. In 2013, Thames Water was classified as being under serious water stress due to climate change and increasing population pressures. In contrast, Severn Trent Water was only moderately stressed (Environment Agency & DEFRA, 2013). For this reason, a strategic water transfer option between the Severn and Thames Basins is under review, with evaluations ongoing of its feasibility to provide reliable water supply for Thames Water customers and the wider South East region during periods of high water stress (Thames Water, 2019c).

5.3 Data and models

This section provides an overview of the data and models used in this study. As parts of the data and modelling framework have been previously been applied elsewhere (Coxon et al. 2019; Dobson et al. 2020; Guillod et al. 2017, 2018), **Section 5.3.1** to **5.3.3** provide abbreviated descriptions of the climatological and hydrological modelling framework. **Sections 5.3.4** and **5.3.5** describe the water system model and infrastructure strategies to be simulated using historical and projected scenarios.

5.3.1 Historical precipitation

Historical precipitation time series used in this study were obtained from the Centre for Ecology and Hydrology (CEH) GEAR 5km resolution historical monthly areal rainfall dataset for the United Kingdom (1890-2017) (Tanguy et al. 2019). Grid points for analysis were selected if they fell within the Thames to Kingston and Severn to Deerhurst catchment boundaries (**Figure 5.1**). Total precipitation for each month in the 127-year period was calculated by adding the precipitation at each grid point within the two catchment boundaries. This resulted in two aggregated catchment time series of monthly precipitation.

5.3.2 Modelled precipitation

A large set of weather sequences from the Weather@Home (W@H) platform are used in this study (Guillod et al. 2017, 2018; Massey et al. 2015), which are generated using a Global Circulation Model (HadAM3P) downscaled with the Met Office Regional Climate Model, HadRM3p, and driven with historic (HadISST) and projected (CMIP5) sea surface temperatures (SST) and sea ice. W@H is a 'citizen science' project that benefits from the unused computing power of thousands of participants to generate large ensembles of

climate model runs. HadAM3P is suited to the W@H platform, representing atmospheric dynamics in the mid-latitudes well compared to other GCMs (Mitchell et al. 2017). HadRM3p is also appropriate for the current application, having reproduced accurate distributions of daily mean temperature and precipitation over Europe (Massey et al. 2015). In recent years the Weather@Home modelling platform has been used to study the impact sea surface temperature driven extreme weather events in England (Haustein et al. 2016), heat related mortality in London and Paris (Mitchell et al. 2016), flood damage in Southern England (Schaller et al. 2016), and national scale drought severity and intensity (Dobson et al. 2020; Rudd et al. 2019). The Weather@Home climate sequences have also been used successfully in a risk-based planning framework in the Thames Basin, reproducing historical weather observations well (Borgomeo et al. 2018).

The Weather@Home dataset contains precipitation (P) and evapotranspiration (PET) time series at a 25km resolution, which is then downscaled to 5km resolution. Precipitation sequences are bias corrected using a linear approach with monthly bias correction factors. The small biases in temperature were not corrected. A complete description of the bias-correction methodology, validation process and resulting data is presented in Guillod et al. (2017, 2018). In summary, the bias correction offers correction for seasonal biases in mean precipitation, but does not affect higher-order moments of the rainfall distribution (Guillod et al. 2018).

This study uses modelled P and PET for the Severn and Thames catchments from the Weather@Home dataset, grouped into three ensembles:

- 100 realisations of the Baseline period (1975-2000), generated using different initial atmospheric conditions, and historic SST and sea ice records from HadISST (Rayner et al. 2003; Titchner & Rayner, 2014);

- 100 realisations of the Near Future period (2020-2049), generated using 50th percentile SST and sea ice projections (CMIP5, (Taylor et al. 2012)) under Representative Concentration Pathway (RCP) 8.5 (Meinshausen et al. 2011);
- 100 realisations of the Far Future period (2070-2099), generated using 50th percentile SST and sea ice projections under RCP8.5.

As with the historical precipitation time series, total precipitation for each catchment is calculated by summing individual precipitation at grid points within the catchment boundaries. The future ensembles are used here to examine the impact of climate change on meteorological, hydrological and water resources drought. Because RCP8.5 represents the upper bound of projected global emissions scenarios, it is appropriate for climate impact assessments focussing on extreme conditions.

5.3.3 Modelled flows

Rainfall-runoff modelling was performed using the DECIPHeR (Dynamic fluxEs and ConnectIvity for Predictions of HydRology) model, developed by Coxon et al. (2019). DECIPHeR is a hydrological modelling framework developed to simulate and predict flows for catchments across multiple spatial scales with different hydrological characteristics. The hydrological model consists of sub-catchment-based hydrological response units (HRUs) which group hydrologically similar areas according to landscape attributes and spatial variability of climatic inputs. HRUs reduce model run time thus allowing for extensive simulations driven by large ensembles of climate conditions (see **Appendix B1**).

The DECIPHeR modelling framework was first used by Coxon et al. (2019) to simulate historic flows at 1366 catchments across Great Britain, performing acceptably against four metrics of model performance. To calibrate the model, historic daily observed

P (Tanguy et al. 2019) and PET (Robinson et al. 2016) were used to run 10,000 model simulations with Monte Carlo sampled parameter sets. Evaluation of the 10,000 simulations showed good model performance across the 1366 flow locations, with 92% of catchments achieving a Nash-Sutcliffe efficiency score greater than zero (Coxon et al. 2019).

DECIPHeR has since been used to generate ensembles of historical and future naturalised flows for 338 catchments across England and Wales (Dobson et al. 2020). The flows were generated using historic daily observed P (Tanguy et al. 2019), PET (Robinson et al. 2016), and the 10,000 parameter sets from Coxon et al. (2019), and were evaluated against daily naturalised flows supplied by England's Environment Agency. The best parameter sets for each catchment were identified according to NSE and logNSE scores, and used to simulate daily flows for the 338 catchments under historic and future climate change projections. This study follows the same hydrological modelling framework outlined by Dobson et al. (2020), using the best DECIPHeR parameter set for the Thames and Severn Basins to simulate historic and future flows. Daily historic flows were simulated using CEH GEAR daily observed P (Tanguy et al. 2019) and PET (Robinson et al. 2016), whilst daily flows for the Baseline (1975-2000), Near future (2020-2049) and Far Future (2070-2099) scenarios were simulated using the Weather@Home projections described in **Section 5.3.2**. **Appendix B1** lists the NSE and logNSE of the calibrated historic DECIPHeR flows for the Thames at Teddington (station 39001) and Severn at Saxons Lode (station 54032; Severn at Deerhurst was not included in the model evaluation).

5.3.4 Water resource modelling, groundwater flows, and water demand

The water system model used in this study of the Severn Trent and Thames Water supply systems has been extracted and adapted from the national water resource model, WREW, presented in Dobson et al. (2020). The Severn Trent Water and Thames Water water resource systems are represented by a series of nodes and arcs in the minimum cost capacitated network flow program model, WATHNET-5 (Kuczera, 1992). The arcs represent flow pathways (rivers and pipes) that connect stream, reservoir, groundwater, demand and waste nodes. In simulation, the model solves a mass balance optimization problem at each time-step, moving water along arcs within the network to minimise demand shortfalls. Each arc is assigned a positive, neutral (zero) or negative cost, which influences the likelihood of flow through an arc. For example, if one water source is more preferable than another it will be assigned a negative cost. Environmental flow arcs are assigned a negative cost to increase the likelihood of a minimum required flow (MRF) being met. Demand shortfall arcs are assigned a very high positive cost, as an incentive for the network flow program to ensure demand is satisfied. In some scenarios a trade-off between demand shortfalls and MRF may emerge. The assumptions made regarding arc cost influence the movement of water throughout the system network. The sensitivity to changes in arc cost assignments are not explored in this study; a notable limitation of the modelling experiment. However, the water system model is a product of collaboration between the University of Oxford and key stakeholders in the UK water industry. Previous work has shown that the model is capable of producing outputs similar to those achieved using water company models (Dobson et al. 2020). It is therefore well suited to climate impact studies such as the one presented in this paper.

The river flows generated by DECIPHeR are used as stream inflows, represented by the crosses in **Figure 5.1**. Groundwater inflows are set at the licence abstraction limit,

defined by the Environment Agency (Environment Agency, 2013b). The reservoirs can directly store stream inflows or by pumped abstractions from rivers, depending on the nature of the infrastructure. The demand nodes act as sinks in the network and represent the demand required from municipal, industrial and agricultural water users. Between 1999 and 2014, agriculture used 3.8% of total surface water abstractions in the Thames, and 2.0% in the Severn. In the same period, public water supply accounted for 88.0% of abstractions in the Thames, and 68.0% in the Severn. The remaining water was used by industry or other abstractors (Environment Agency, 2013b). Historical demand is estimated using dry year annual average distribution input at water resource zone level and annual demand profiles, and paired with the historic CEH GEAR-DECIPHeR flow scenario. Ten scenarios of future municipal water demand for each water company are estimated from the dry year annual average distribution input at water resource zone level and scaled according to Severn Trent and Thames Water water resource planning tables and demand profiles (Severn Trent Water, 2019; Thames Water, 2019a). Differences in projected demand scenarios typically result from (i) different rates of population growth and (ii) changes in per capita consumption (Beh et al. 2014). The range of projected demand is presented in **Appendix B2**. Each future demand scenario is coupled with the 100 Baseline, Near Future and Far Future DECIPHeR flow scenarios, to create a library of 3000 scenarios (total of 85,000 simulation years). WATHNET-5 is used to simulate the water resource system at a daily time-step under different climate and demand scenarios. Simulation output can include demand deficits, end of step reservoir storage and frequency of water restrictions imposed on customers.

5.3.5 Water transfer strategies

The main infrastructure option to be evaluated is the proposed raw water transfer from Deerhurst on the River Severn to a location in the Upper Thames catchment. Five transfer capacities are evaluated. The first four tested (300, 500, 700 and 900 mega-litres per day (Ml/d)) are limited by the infrastructure capacity to move the water i.e. the size of the pipe. The 300 and 500Ml/d transfers are based on the Water Resource Management Plan 2019 (WRMP19) planning options (Thames Water, 2019a), with the larger 500Ml/d capacity transfer being supported by redeployment of 200Ml/d of water from the Vyrnwy Reservoir in the Severn headwaters. The 700 and 900Ml/d transfers are evaluated to assess the impact of larger capacity transfers during future drought scenarios, though these larger transfers are not currently being considered by Thames Water or Severn Trent Water due to environmental challenges. Transfer capacities of this size are uncommon, although not unheard of in water resource planning assessments. For example, following the 2004-2006 drought an investigation was launched into large-scale water transfers in the UK, assessing the feasibility of a multi-pipe 1100 Ml/d transfer from the Northern Pennines (North West England) to London. Findings indicated that the financial cost of large-scale transfers would greatly exceed costs of regional capacity expansion options, but transfers of this scale may be necessary if water companies' existing resource management plans prove inadequate in the face of future water supply and demand pressures (Environment Agency, 2006). For context, 900Ml equates to (i) approximately 0.3% of the combined volume of reservoirs in the Severn water supply system, and 0.41% of the combined reservoirs in Thames Water, and (ii) approximately 71% of historical daily demand in Severn Trent and 35% in Thames Water (estimated from simulation of the water system model from 1962-2015 using historic CEH GEAR climate sequences).

The final transfer option assumes unlimited capacity, so all flows above the 1800 Ml/d MRF (Environment Agency, 2014) in the Severn at Deerhurst can be transferred to the Thames Basin. This option is included in the analysis (i) to identify the volumes of water that would be taken for use in the Thames Water system if no infrastructural, financial or environmental constraints existed, and (ii) to explore the impact this would have on hydrology and customer service in the Severn. Importantly, the strategy is purposefully experimental in design and bears no resemblance to real world transfers. The operation is coded to minimise the frequency with which the flows at Deerhurst fall below the MRF, and as a consequence may result in some days when flow fails to meet the MRF.

We also test strategies in which there is a new reservoir situated in the Upper Thames Basin, to explore the value of additional storage in the Thames Water system working in tandem with the transfer scheme. This reservoir (South East Strategic Reservoir) is also being considered by Thames Water as a feasible planning option to manage future climate change and demand side pressures (Thames Water, 2019a). The new reservoir has an initial storage of 75,000Ml and the operating rules governing inflow into the reservoir and releases from the reservoir are based on rules used for the London reservoirs.

Three transfer operating rules are investigated. The first rule (unconditional) allows Thames Water to use the volume of water equivalent to total capacity of the transfer as frequently as is needed, limited only by water availability in the Severn Basin. This rule ignores the consequences of taking water that could otherwise be used by Severn Trent Water and is consistent with Lund & Israel's definition of a permanent transfer, which "involves the acquisition of water rights and a change in ownership of the right" (Lund & Israel, 1995b). The second rule (conditional) only allows transfer of water left over in the Severn at Deerhurst, after all of the water requirements in Severn Trent have been satisfied.

This rule is aligned with common riparian water rights, as Severn Trent does not need to guarantee water availability for Thames Water, but should ensure that the flow and quality of transferred water remains acceptable (regardless of volume or timing). Rule two is designed to ensure that Severn Trent Water customers are not subject to decreased water supply in order to provide for Thames Water. The third rule (shared risk) follows the same principles of rule one, but also assumes that whenever Thames Water experience a severe water restriction, Severn Trent must impose an equivalent water restriction. This is to encourage full cooperation (i.e. maximum transfer deployment) between the two companies during periods of high drought risk in the Thames. Rule three does not follow traditional riparian rights doctrine and, like the unlimited transfer strategy, is experimentally designed to investigate the impact of this management style on water system performance under drought.

The transfer strategies are outlined in **Table 5.1**. In the water system model, the transfer arc connecting the Severn and Thames water resource systems is assigned a positive cost to ensure that water is only transferred when it is beneficial for the receiving region.

Table 5.1. Transfer strategies to simulate under future flow and demand scenarios. Feasible WRMP19 Option denotes options which were considered feasible in Thames Water's 2019 Water Resource Management Plan.

Strategy Code	Transfer Capacity (Ml/d)	Upper Thames Reservoir	Operation	Feasible WRMP19 Option?
0	0	×	-	-
300.U	300	×	Unconditional	Yes
500.U	500	×	Unconditional	Yes
500.R.U	500	✓	Unconditional	Yes
300.R.U	300	✓	Unconditional	Yes
300.C	300	×	Conditional	Yes
500.C	500	×	Conditional	Yes
500.R.C	500	✓	Conditional	Yes
300.R.C	300	✓	Conditional	Yes
300.S	300	×	Shared Risk	Yes
500.S	500	×	Shared Risk	Yes
500.R.S	500	✓	Shared Risk	Yes
300.R.S	300	✓	Shared Risk	Yes
700.R.U	700	✓	Unconditional	No
700.R.C	700	✓	Conditional	No
700.R.S	700	✓	Shared Risk	No
700.U	700	×	Unconditional	No
700.C	700	×	Conditional	No
700.S	700	×	Shared Risk	No
900.R.U	900	✓	Unconditional	No
900.R.C	900	✓	Conditional	No
900.R.S	900	✓	Shared Risk	No
900.U	900	×	Unconditional	No
900.C	900	×	Conditional	No
900.S	900	×	Shared Risk	No
Unlim.R.U	Unlimited	✓	Unconditional	No

5.4 Methodology

5.4.1 Overview of workflow

Figure 5.2 provides an overview of the workflow used in this study. The framework uses a large ensemble of climate scenarios containing a wide array of drought events and multiple demand scenarios. The workflow provides a mechanism to explore drought impacts on transfer reliability, water supply and water use restrictions. The methodology is also designed to investigate how spatial patterns of drought may change throughout the 21st Century, and how this may impact cooperation between water companies operating in neighbouring basins.

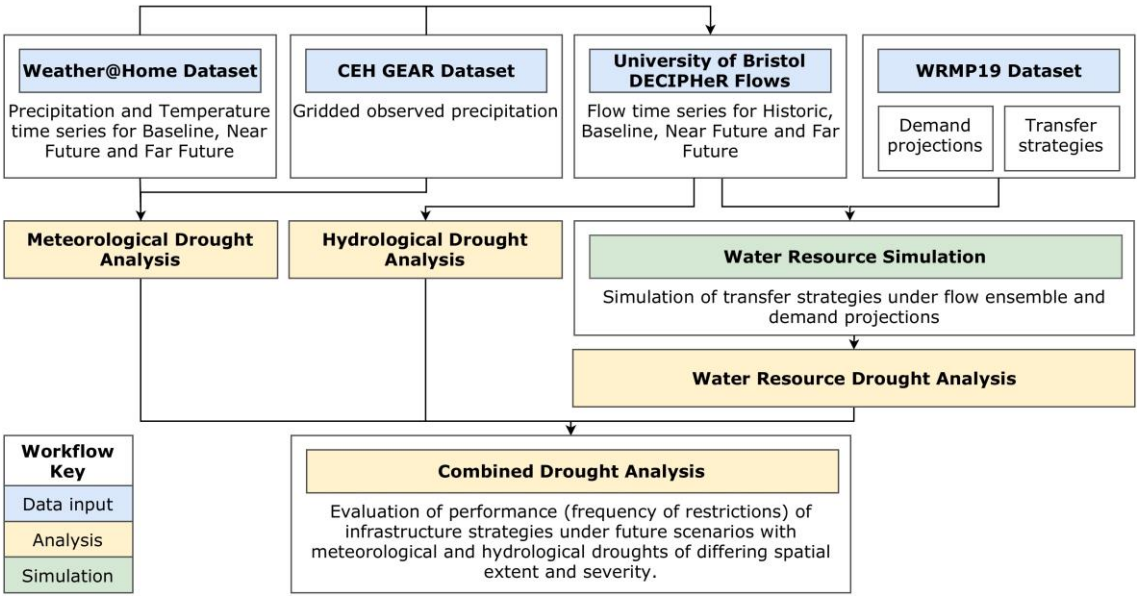


Figure 5.2. Workflow with data sources, scenarios and model outputs.

5.4.2 Meteorological drought analysis

Standardized Precipitation Index (SPI) is used to classify meteorological drought within the two study catchments. The index identifies the relative departures of precipitation from normality for a given location, and has been widely used to identify drought events (Bayissa et al. 2018; Hannaford et al. 2011) and analyse the spatial patterns of drought (Fleig et al. 2011; Vicente-Serrano, 2006). The index is calculated following the sequence outlined by McKee et al. (1993), using a monthly precipitation time series (**Appendix B3**). Calculated SPI values are scale-independent, fluctuating between negative (dry periods) and positive (wet periods) values. This makes SPI ideal for spatial analyses of drought in across multiple locations.

SPI is commonly used as an indicator of drought intensity over a specific time period. Here, intensity is represented by the degree of precipitation deficit i.e. the value when the index is below zero. The values can be classified to represent different categories of meteorological drought, as shown in **Table 5.2**. For short time-scales (1 to 6 months) the index is expected to fluctuate at a high frequency and is suitable for identifying soil

moisture deficits and agricultural droughts. SPI fluctuates at a lower frequency for longer time-scales and is more indicative of changes to surface water resources (Edwards & Mckee, 1997). In the context of the framework presented here, we are interested in choosing an index time-scale that reflects the state of water resource supplies in the study area(s). This study therefore uses 12-month observation periods to classify meteorological drought. As Dobson et al. (2020) demonstrate in their spatial analyses of drought and water scarcity, a 12-month observation period is well suited to identifying meteorological and hydrological droughts that impact water resource supplies in England and Wales (Dobson et al. 2020). In addition to this, 12-month lags are commonly used in drought analyses by water industry practitioners (e.g. Hunt & Wade, 2016). However, the proposed framework lends itself to additional investigation into the relationship between water system state and drought indices of a shorter period. For instance, shorter time-scales may be more relevant for regions without significant water supply storage infrastructure, as short-term rainfall will be more relevant for the planning issues faced by water managers.

Table 5.2. Drought categories as defined by SPI value (McKee et al. 1993).

SPI Value	Drought Category
Less than or equal to -2	Extreme
-1.99 < 1.5	Severe
-1.49 to -1.00	Moderate
-0.99 to 0	Near normal or mild

To calculate SPI, aggregated monthly precipitation series from the historic CEH GEAR and W@H data sets are first formatted for the two catchments. The GEAR dataset is used to define Gamma parameter estimates for averaging periods in both catchments, which are then used to calculate the cumulative distribution of the precipitation datasets and subsequently standardized precipitation indexes. The resulting dataset contains catchment

specific SPI time series for the historic record and the W@H ensemble (total of 301 time series per catchment).

The method outlined by Rahiz & New (2012) is used here to examine the coincidence of major droughts in the Severn and Thames. This approach identifies scenarios within the ensemble containing meteorological droughts occurring simultaneously in both catchments that are equal to or worse than the 5th, 10th and 25th percentile drought intensities in the Baseline ensemble. The library of coincident drought events is analysed to provide an estimate of the probability of coincident drought for the Baseline, Near Future and Far Future ensembles and indicate how the spatial patterns of meteorological drought with different intensities may change into the future.

5.4.3 Hydrological drought analysis

12-month Standardized Runoff-discharge Index (SRI) is used to identify hydrological drought events in the historical and future DECIPHeR flow ensembles. The process to calculate SRI is akin to the SPI calculation using a distribution to fit observed or modelled flow data. Research has shown that parameter distributions should well represent seasonal streamflow regimes and extreme flows (Vicente-Serrano et al. 2012). This is especially important for studies using short-term drought indices (1-, 3- and 6- month), which are more susceptible to seasonal changes. As this study examines 12-month lag SRI, it is not necessary to vary the distribution intra-annually to take into account seasonality.

In line with the process described in **Section 5.4.2**, we use a Gamma distribution to calculate SRI. Previous research has used a Gamma distribution to define streamflow in the Feather River Basin in California (Shukla & Wood, 2008), and for multiple catchments across England and Wales (Dobson et al. 2020). Here, SRI is calculated at a 12-month lag for the Severn at Deerhurst (NRFA station 54110) and the Thames at Kingston (NRFA

station 39001), which are the most downstream locations in each basin that can be represented in the DECIPHeR model. To obtain flows for the Severn at Deerhurst we aggregate data from two inflow points upstream of Deerhurst (Severn Bewdley incremental and Avon Incremental); for the Thames at Kingston we use the data from the Teddington Weir inflow point. A one-sample Kolmogorov-Smirnov (KS) test is used to ensure that a Gamma distribution is suitable to define streamflow and precipitation in the two study regions. The KS test evaluates the hypothesis that the calculated historic SRI and SPI time series come from a standard normal distribution (**Appendix B3**).

We use the historic CEH GEAR driven DECIPHeR flows (1962-2015) to define the Gamma parameter estimates used in the SRI calculation. This is because the recorded observed flow at Deerhurst gauging station contains only 17 years of flow (1995-2012) and has two extended periods of missing data in 2007 and 2011 (NERC CEH Wallingford, 2018). The resulting dataset contains catchment specific SRI time series for the historic record and the W@H ensemble (total of 301 time series per catchment).

5.4.4 Water resource drought analysis

When reservoir levels are low, water companies can impose restrictions on water use as part of their drought plans. The frequency of water use restrictions of given levels of severity imposed upon customers is used as a metric of water shortages in the Severn Trent and Thames Water regions (**Table 5.3**). Level 1 and 2 restrictions are fairly modest and do not represent a significant hardship or economic loss to most water users, but Level 3 restrictions are more severe and Level 4 restrictions are considered to be extreme. Restrictions are imposed based on the current storage of key reservoirs within the water system (**Figure 5.3**) In Severn Trent Water, restriction level is determined by water levels of the Elan Valley and Derwent Water reservoirs; in Thames Water it is dependent on the

combined water levels of the London Storage reservoirs. To avoid imposing unnecessary restrictions to their customers, Severn Trent Water can draw water from other reservoirs in the Severn system (Blithfield, Draycote, Clywedog, Carsington and Ogston, Melbourne, Cropston and Thornton) before the Elan and Derwent reservoirs are allowed to fall below the thresholds for water restrictions. This is in contrast to the Thames system, which contains no other regulating reservoirs (Thames Water's Oxfordshire reservoir, Farmoor, cannot be used to alleviate water restrictions in London). We use the WATHNET-5 model to calculate the frequency of water restrictions being imposed in the two regions. The simulation results are then used to identify transfer strategies that reduce the probability of restrictions.

Table 5.3. Example of levels of water use restrictions to customers in Thames Water and Severn Trent Water (Severn Trent, 2019; Thames Water, 2019a).

Severity of restriction	**Measures for domestic customers**	**Expected frequency of occurrence in Thames**	**Expected frequency of occurrence in Severn**
Level 1	Intensive water saving media campaign	1 in 5 years	N/A
Level 2	Partial hosepipe ban & media campaign	1 in 10 years	N/A
Level 3	Temporary use ban and non-essential use ban	1 in 20 years	3 in 100 years
Level 4	Extreme restrictions (standpipes, rota cuts)	1 in 100 years	No planned frequency

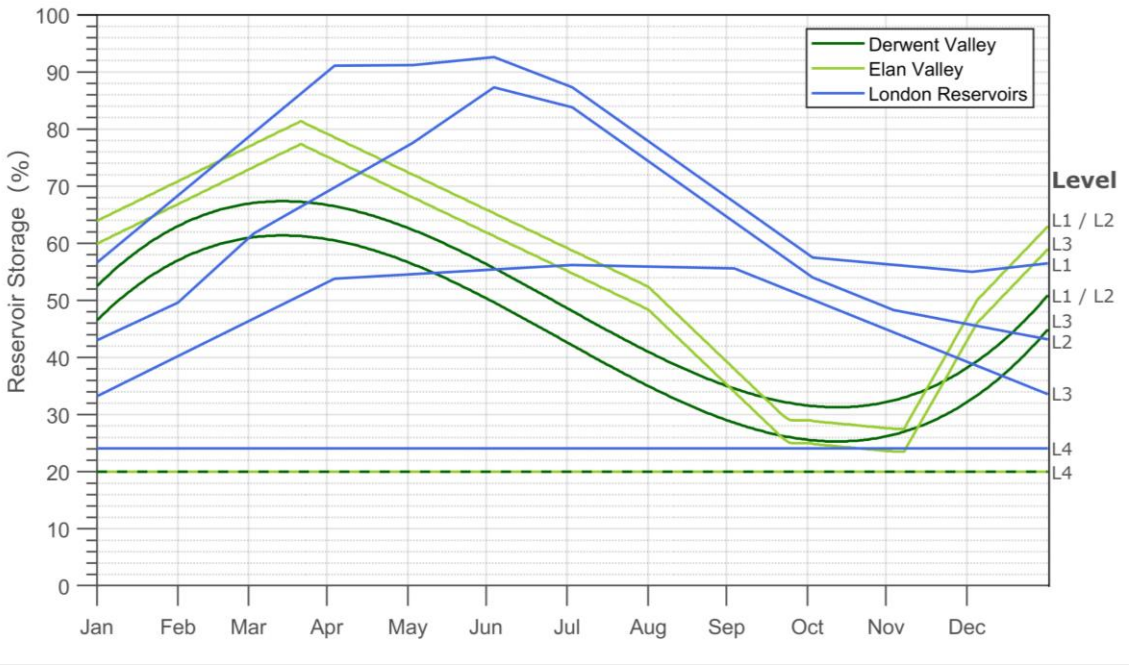


Figure 5.3. Control diagram for Derwent Valley, Elan Valley and London Reservoirs showing reservoir levels resulting in water restrictions to public water customers.

Coincident water resource drought is calculated using a similar methodology as hydrological and meteorological coincident drought, identifying periods within the simulation when Severn Trent and Thames Water are exposed to water restrictions in the same month. Simulation will reveal how the occurrence of coincident water resource drought change with different transfer strategies through time.

5.5 Results

5.5.1 Meteorological drought

Table 5.4 depicts the probability of drought months in the CEH GEAR and W@H ensembles with an SPI value equal to or worse than the 5th, 10th and 25th percentiles in the W@H Baseline ensemble for each catchment. Here, values below the 5th percentile represent severe and extreme droughts, below the 10th percentile represent moderate

drought (or worse), and below the 25th percentile represent mild drought (or worse). For the Severn to Deerhurst this includes drought months with an intensity equal to or less than -1.84, -1.42 and -0.74 respectively, and in the Thames to Kingston months less than or equal to -1.57, -1.18 and -0.56 respectively. The results indicate that the number of months with SPI values worse than the Baseline ensemble will increase into the future for both catchments, more so for the Severn to Deerhurst than the Thames to Kingston. The results also suggest that the W@H Baseline ensemble contains fewer mild, moderate and severe meteorological drought events in the Severn than the CEH GEAR dataset (Historic), but more in the Thames catchment.

Table 5.4. Probability of months in Historic (CEH GEAR), Baseline, Near Future and Far Future ensembles with 12-month SPI values less than W@H Baseline 5th, 10th and 25th percentiles for Thames and Severn study areas, individually and simultaneously.

Percentile	Basin	Historic	Baseline	Near Future	Far Future
Severe (5th)	Severn	0.037	0.050	0.088	0.168
	Thames	0.058	0.050	0.081	0.161
	Severn & Thames Simultaneously	0.027	0.030	0.056	0.114
Moderate (10th)	Severn	0.083	0.100	0.159	0.273
	Thames	0.119	0.100	0.151	0.263
	Severn & Thames Simultaneously	0.061	0.066	0.110	0.200
Mild (25th)	Severn	0.226	0.250	0.343	0.497
	Thames	0.274	0.250	0.322	0.477
	Severn & Thames Simultaneously	0.192	0.184	0.261	0.402

Table 5.4 also lists the probability of months in the W@H ensembles with an SPI value less than the W@H Baseline 5th, 10th and 25th percentiles in both catchments in the same month. Coincident drought occurrence also increases into the future, with over one in ten months in the Far Future ensemble experiencing a severe drought simultaneously in the

Thames and Severn catchments. The frequency of mild droughts also increases into the future, with roughly 40% of all months in the Far Future ensemble experiencing SPI values worse than the historic 25th percentile. This means that two in five months experienced SPI values less than -0.74 in the Severn to Deerhurst catchment and -0.56 in the Thames to Kingston catchment simultaneously. **Figure 5.4a**, **c** and **e** show that the changing spatial dependence of meteorological droughts across both basins is the main driver for increased drought frequency. The area under the curve gives the probability of any given month in each W@H ensemble experiencing a severe (**a**), moderate (**c**) or mild (**e**) meteorological drought in only one or both catchments. The area is divided into three segments: the top segment (light green) represents the probability of any given month in each ensemble experiencing a drought of given severity in the Severn, but not in the Thames catchment; the middle segment (blue) represents the probability of any given month in each ensemble experiencing a drought of given severity in the Thames, but not in the Severn catchment; the bottom segment (orange) shows the probability of a coincident drought of the same severity occurring. The complete set of results from the non-coincidental meteorological drought analysis is presented in **Appendix B4**. The plots show that, for all drought severities, the increase in drought occurrence is caused by a large growth in the probability of coincident droughts. This suggests that meteorological droughts will become more spatially coherent throughout the 21st Century.

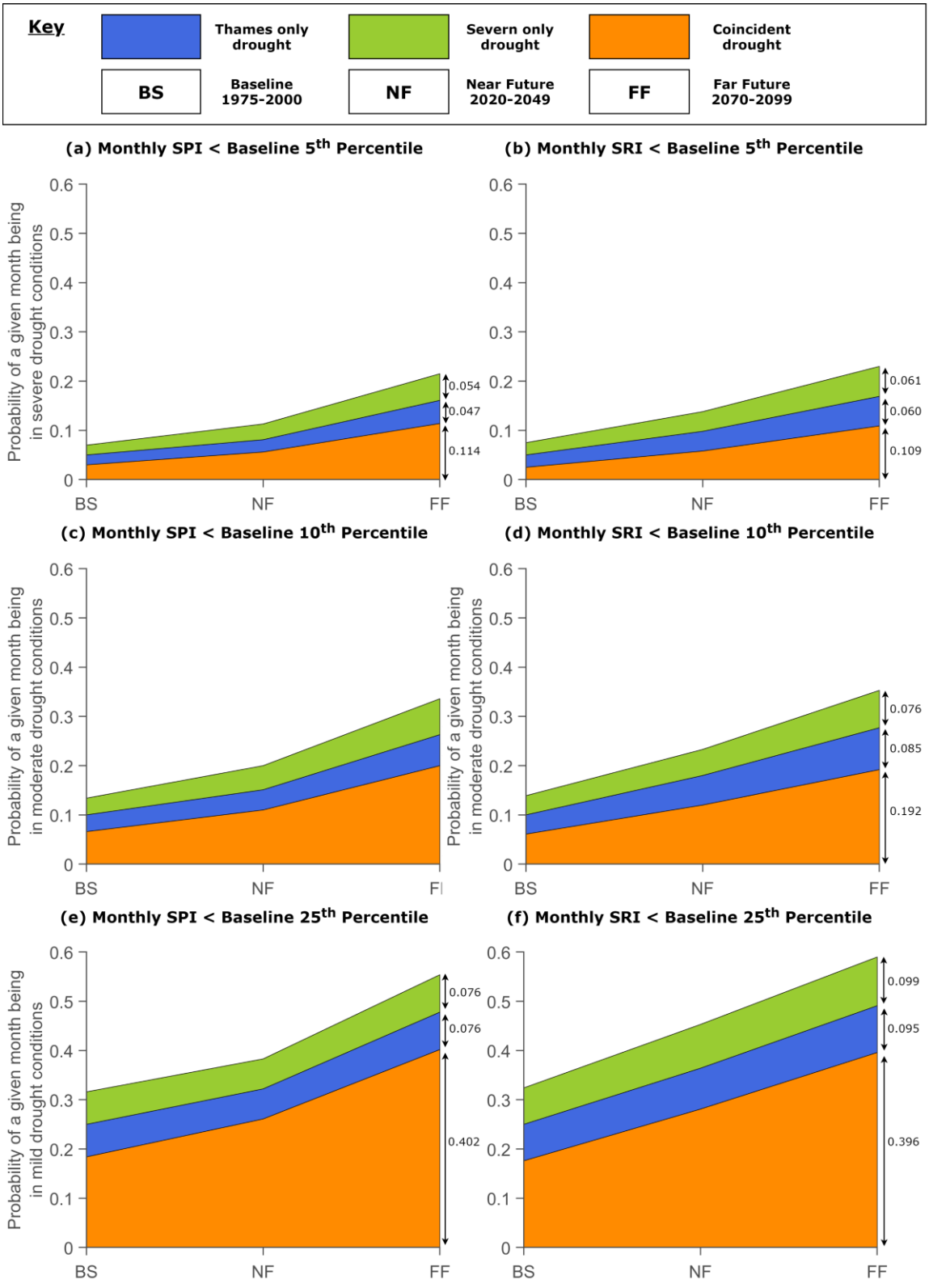


Figure 5.4. Stacked bar graph showing probability of coincidental and non-coincidental metrological (**a**, **c**, **e**) and hydrological (**b**, **d**, **f**) drought events of different severities occurring throughout the W@H future.

5.5.2 Hydrological drought

12-month SRI time series were calculated using DECIPHeR flows for the Thames at Kingston and Severn at Deerhurst. The SRI values generated with the CEH GEAR DECIPHeR flow time series are compared to the W@H ensemble driven DECIPHeR flows. **Table 5.5** shows the probability of hydrological drought months in the flow ensembles with an intensity equal to or worse than the 5th, 10th and 25th percentiles in the Baseline flows. In both catchments 12-month SRI values increase at a similar degree as 12-month SPI, which suggests that projected changes in precipitation and streamflow are closely related. However, unlike SPI, all severities of SRI drought events in the CEH GEAR time series (Historic) are less probable than the W@H Baseline, a likely consequence of parameterisation in the hydrological modelling. Future work could explore the sensitivity of hydrological drought severity and frequency to parameter set choice.

The similar values of coincident drought listed in **Table 5.5** for the Historical and Baseline ensemble indicate that the DECIPHeR flows reproduce both independent and cross catchment features of the two regions well. Consistent with the SPI analysis presented in **Section 5.5.1**, these results suggest an increase in severe coincident hydrological drought throughout the 21st Century, with coincident drought in the Near Future ensemble occurring more than double the frequency than coincident drought in the Baseline ensemble, and over four times more often in the Far Future. Moreover, mild coincident hydrological drought (25th percentile) occurs nearly once every three months in the Near Future ensemble and every two in five months in the Far Future ensemble. This will likely have a drastic impact on water supply and service to customers.

Table 5.5. Probability of months in Historic, Baseline, Near Future and Far Future flow ensembles with 12-month SRI values less than W@H Baseline 5th, 10th and 25th percentiles for Thames and Severn study areas, individually and simultaneously.

Percentile	Basin	CEH GEAR	Baseline	Near Future	Far Future
Severe (5th)	Severn	0.028	0.050	0.097	0.169
	Thames	0.039	0.050	0.098	0.168
	Severn & Thames Simultaneously	0.011	0.025	0.058	0.109
Moderate (10th)	Severn	0.088	0.100	0.172	0.267
	Thames	0.091	0.100	0.180	0.275
	Severn & Thames Simultaneously	0.047	0.061	0.120	0.192
Mild (25th)	Severn	0.231	0.250	0.370	0.493
	Thames	0.164	0.250	0.364	0.489
	Severn & Thames Simultaneously	0.131	0.176	0.281	0.396

Figure 5.4b, **d** and **f** support the hypothesis that an increased spatial coherence of hydrological droughts is the main driver for the increase in drought frequency throughout the 21st Century. The complete set of results from non-coincident hydrological drought analysis is presented in **Appendix B5**. The plots show that for all drought severities the increase in probability of hydrological droughts is caused by a large rise in coincident droughts. The results suggest that the likelihood of droughts occurring in one basin but not the other will remain fairly constant throughout the 21st Century, whilst droughts affecting both catchments simultaneously will become more common. Again, this will impact the operation and success of inter-basin transfers reliant on movement of water during high stress periods.

5.5.3 Water resource drought

The 26 transfer strategies were simulated in WATHNET-5 at a daily time-step against the library of DECIPHeR flows and demand scenarios. The level of water restrictions in

Severn Trent Water and Thames Water is recorded at the end of each time-step and results are aggregated to a monthly time-scale in post-processing.

Figure 5.5 shows the probability of a month with water restrictions (any level and severe), for both companies and for the different transfer strategies. A complete set of restriction analysis results and visualisation of transfer strategy impact can be found in **Appendix B6**. In the absence of any interventions by Thames Water, the probability of water restrictions increases considerably from the Historic and Baseline scenarios to the Near Future and Far Future scenarios, unlike in Severn Trent where the increase in the frequency of restrictions is projected to be less.

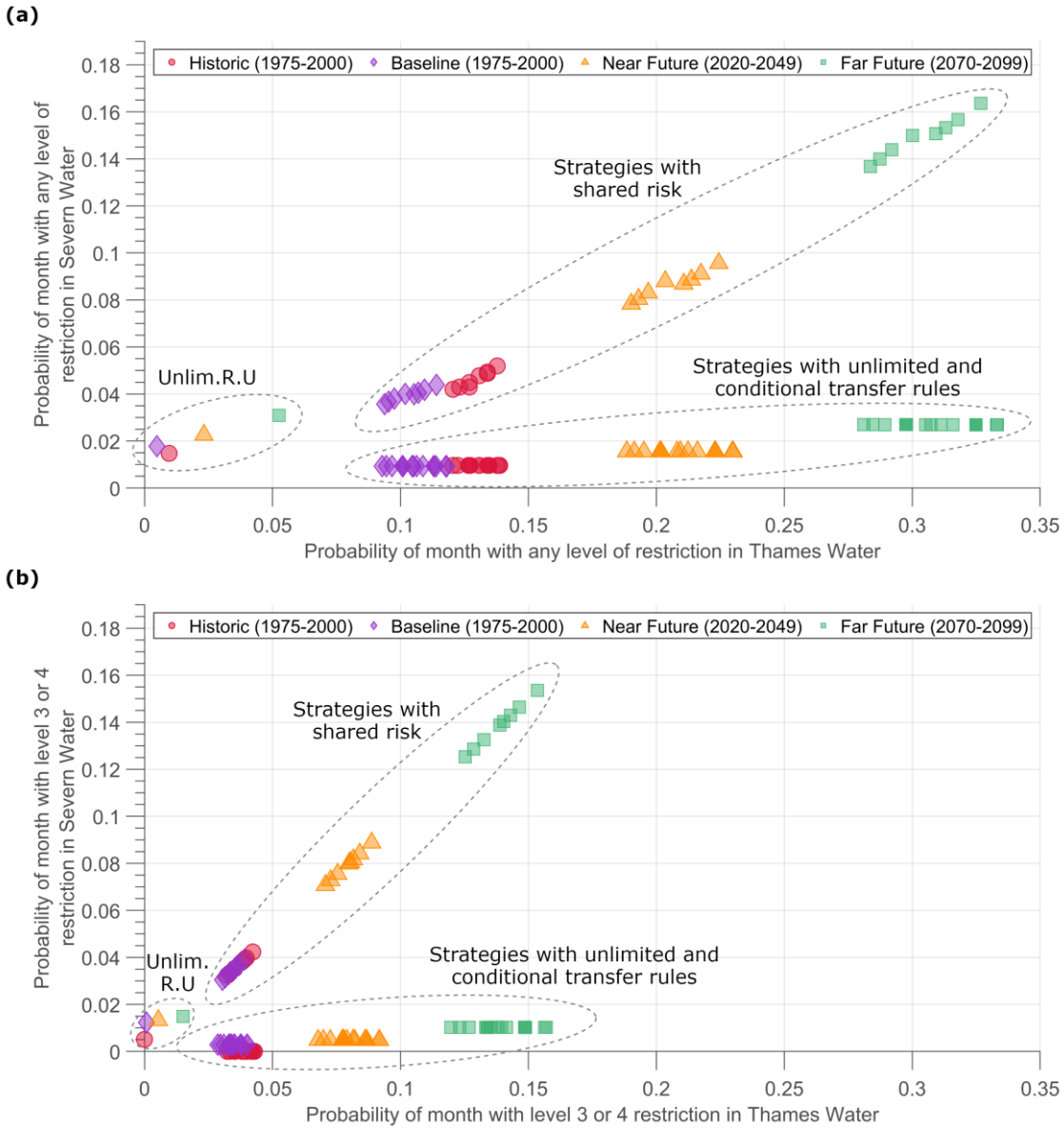


Figure 5.5. Probability of Thames and Severn experiencing any level of water restriction (**a**) and severe / level 3 and level 4 water restrictions (**b**) in any given month for each infrastructure strategy in Historic (circular markers, red), Baseline (diamond markers, purple), Near Future (triangular markers, orange) and Far Future (square markers, green).

The introduction of transfer infrastructure has varying effects on the frequency of restrictions. Strategies operated with the conditional and unconditional rules show little impact to restriction frequency in Severn Trent, which suggests that the loss of water in the Severn water system to Thames Water is not large enough to impact the overall

reliability of water supplies. Surprisingly, even the largest capped capacity transfer (900Ml/d) fails to influence the frequency of water shortages in the Severn water system. This is likely due to the large headwater reservoirs in the Upper Severn catchment, which can release flows to balance demand further downstream. The greatest variation in impact to Severn Trent under the conditional and unconditional rules is observed in the Far Future ensemble, although this is on the magnitude of 0.0001 probability. In contrast, transfer infrastructure significantly benefits the reliability of water supplies in Thames Water, with improvements in all strategies compared to no transfer. The strategies that produce the greatest decreases in probability of restrictions are a product of greater connectivity of supply between the two river basins and increased capacity to store the transferred water in the new Upper Thames reservoir. Strategy 300.C is the least successful strategy for Thames Water, producing similar probabilities of restrictions to Strategy 0. This suggests that the small capacity of water available to Thames Water via the conditional transfer is ineffective during high drought risk periods.

Because the 'shared risk' (e.g. 300.S) strategies impose restrictions on Severn Trent when restrictions are required in the Thames, these strategies increase probability of restrictions four-fold for Severn Trent. The frequency of these restrictions is sensitive to the size of the transfer simply because larger transfers result in less frequent restrictions in the Thames. This 'shared risk' strategy does not improve performance in Thames Water as the benefit is governed by the size of the transfer infrastructure and storage reservoir, rather than water availability in the Severn.

Figure 5.6 illustrates the probability of severe restrictions occurring simultaneously in both water companies. Note that due to the logarithmic scale on the y-axis, probabilities of zero are not plotted. Therefore, strategies in the historic simulation with no severe restrictions are not shown on the plot. Complete results of water resource

drought coincidence analysis can be found in **Appendix B7**. As with SPI and SRI, probability of coincident water resource drought increases into the W@H future. Consistent with the results presented in **Figure 5.5**, the shared risk strategies (e.g. 300.S) result in high probabilities of coincident restrictions compared to conditional (e.g. 300.C) and unconditional (e.g. 300.U) transfers.

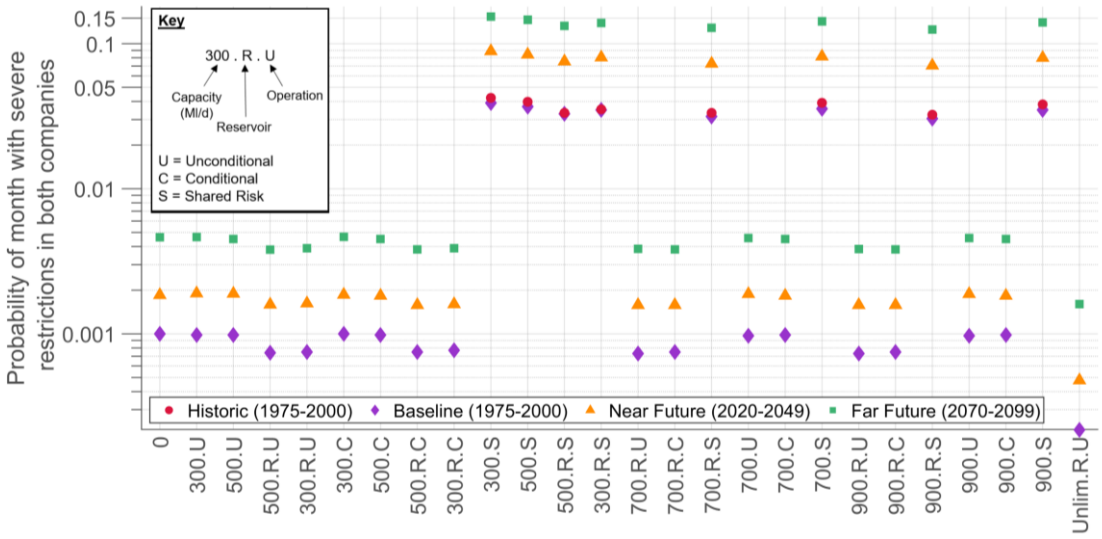


Figure 5.6. Probability of Thames and Severn water resource regions experiencing a severe water restriction simultaneously in any given month in the Historic (circular markers, red), Baseline (diamond markers, purple), Near Future (triangular markers, orange) and Far Future (square markers, green) ensembles.

For the unconditional and conditional transfers, the probability of severe restriction based coincident drought is proportionally less than the other drought indicators; an artefact of the methodology (fewer severe restrictions being imposed in Severn Trent). Measures of coincidence show less variance between transfer strategies, particularly for the Historic and Baseline ensembles. The inclusion of the Upper Thames reservoir decreases the probability of coincident restrictions in all three W@H ensembles, again consistent with

Figure 5.5. This suggests that the increased storage in the Thames Water supply system helps to reduce the frequency of restrictions, and therefore reduces the overall likelihood of restrictions occurring coincidently with Severn Trent. The results also suggest that both transfer agreements without additional capacity and reservoir storage provide little additional benefit in reducing coincident water restrictions.

To explore the maximum potential benefit of a transfer to Thames Water, the Unlim.R.U strategy was also simulated against the library of flow and demand ensembles. This strategy simulates an unlimited capacity transfer, which allows the transfer of all flows above the MRF in the Severn at Deerhurst to the Upper Thames catchment, and occasionally flows below the MRF. The exceedance curves and statistics for the volume of water transferred under Unlim.R.U are shown in **Figure 5.7**. The curves represent volume transferred across the full ensemble; cdfs for individual scenarios are presented in **Appendix B8**. Note volumes equal to zero (days when no water is transferred) are omitted on the graph; a consequence of the logarithmic scale on the y-axis. The plot suggests that the mean volume of water transferred will decrease into the future, a likely consequence of the increased frequency of hydrological droughts, whilst maximum single transfers will increase by the end of the century. These massive transfers at the upper end of the curve occur during high flow periods in the Severn, with 99% of the transfers in the Far Future ensemble equal to or greater than 10,000Ml/d taking place when flow upstream of the MRF at Deerhurst is higher than 20,000Ml/d. Indeed, transfers of this size could significantly alter the hydrology and, depending on the timing of the transfer, increase the risk of flooding in the receiving region. This reason, in addition to environmental constraints, makes the unlimited transfer is an infeasible solution for the supply and demand side pressures faced by Thames Water.

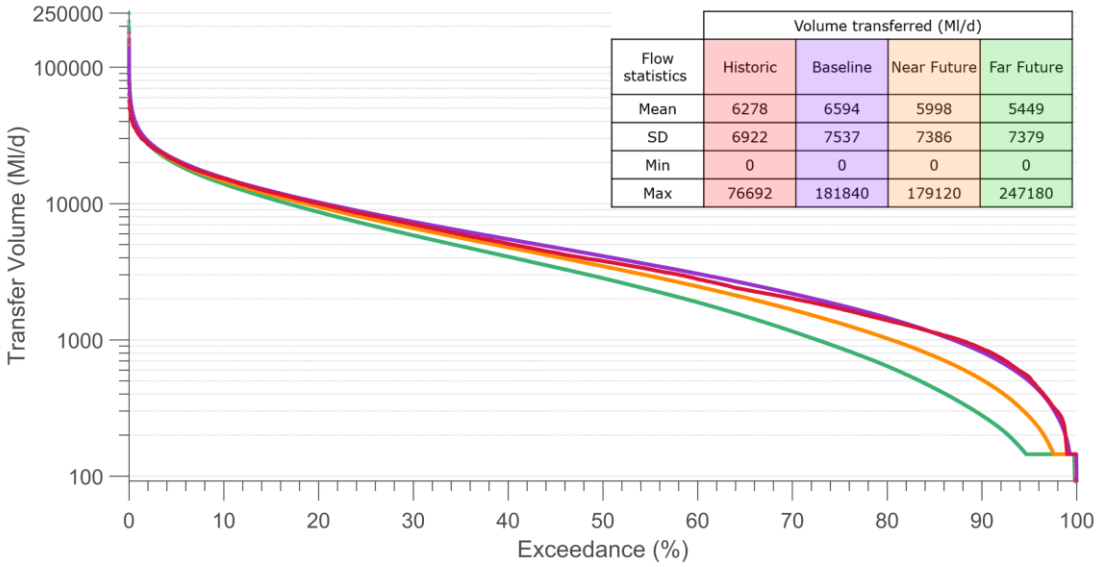


Figure 5.7. Exceedance curves and statistics for volume of transferred water under Unlim.R.U. for each flow ensemble (Historic – red, Baseline – purple, Near Future – orange, Far Future – green).

Each curve features a distinct plateau between 100 and 200 Ml/d, which is caused by the MRF at Deerhurst. In nearly all scenarios, the MRF is met because environmental flows at Deerhurst are prioritised in the water allocation, so water is allocated to meet the environmental flows before any is transferred. However, in the most extreme low flow scenarios, the MRF is not met. **Figure 5.7** shows that there is a very low probability of the transfer continuing to transport water to the Upper Thames catchment despite the MRF at Deerhurst not being met, and that the likelihood of this occurring increases with time. This happens only in a limited number of scenarios under exceptional circumstances when a severe drought order permits the violation. Under these scenarios, the network flow optimization in WATHNET-5 has to balance between the penalty incurred during an extreme demand shortfall in the Thames system and the penalty incurred for violating the environmental flow requirement at Deerhurst. This trade-off reflects the situation that

water managers face during droughts when they may be permitted to violate environmental flow requirements but are reluctant to do so. As the simulations show, the probability of this is very low, but is possible in extremely dry, high demand scenarios.

Figure 5.8 displays the exceedance curves of the flow at Deerhurst after the transfer abstraction point for the Baseline, Near Future and Far Future simulations. The plots illustrate the impact of an unlimited capacity transfer on minimum flows at Deerhurst. For 0.002% of the time in the Baseline, 0.039% in the Near Future and 0.145% in the Far Future ensembles the flow would be equal to or less than the MRF, compared to 0.001%, 0.014% and 0.101% under Strategy 0 (respectively). Consistent with **Figure 5.7** the curves plateau at the MRF, again a consequence of the minimum flow requirement at Deerhurst, which prioritises the environmental flow below the transfer abstraction point over demand in all but a few scenarios. The curves reiterate the increasing likelihood of the MRF at Deerhurst not being met with time, and that this becomes more likely under the unlimited transfer strategy. Future changes to environmental regulation or river abstraction allowances (Environment Agency, 2019a) could limit the projected impacts on flow below Deerhurst, although this is not explored in the modelling framework used here.

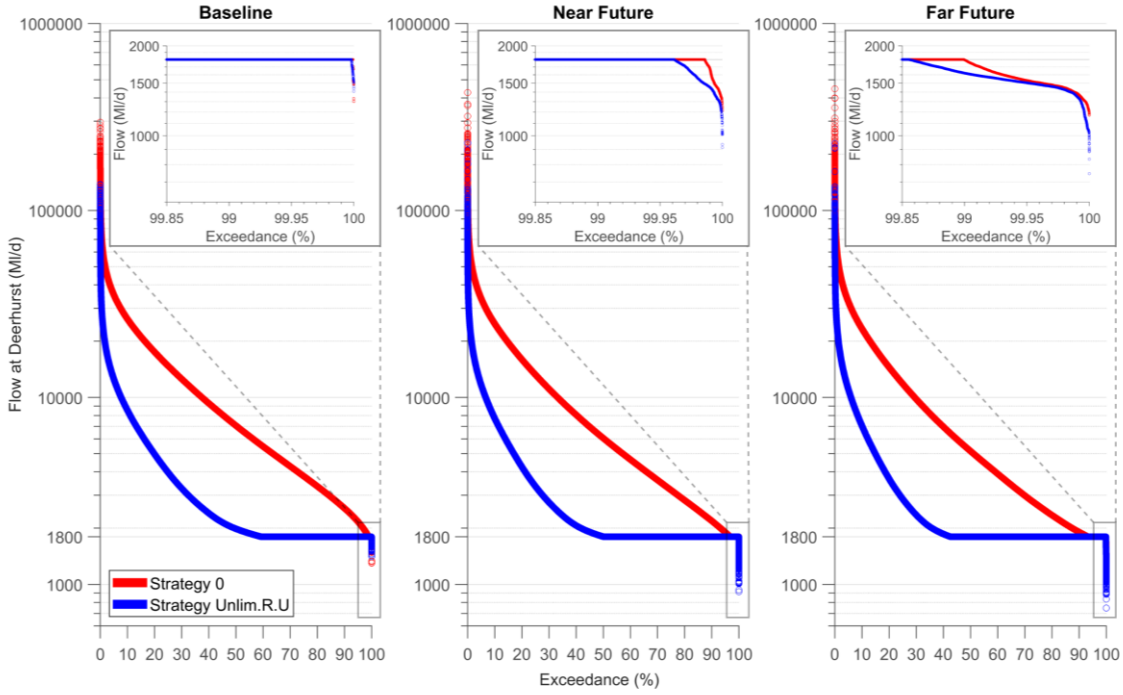


Figure 5.8. Exceedance curves of flow at Deerhurst below transfer abstraction point for Strategy 0 and Strategy Unlim.R.U when simulated against W@H flow ensembles and demand projections in WATHNET-5. Minimum required flow (1800 Ml/d) at Deerhurst is marked on the maximised plots of the lower end of the exceedance curve.

Simulations using the Far Future ensemble indicate that probability of severe restrictions in Thames Water could reduce from 0.157 under Strategy 0 to 0.0151 under Unlim.R.U. This is in contrast to severe restrictions in Severn Trent, which see an increase in likelihood from 0.0102 (Strategy 0) to 0.0149 (Unlim.R.U). This trade-off in risk is due to the unconditional transfer operating rule in Unlim.R.U, which does not prioritise supply to Severn Trent demand centres (nodes in the simulation model) over Thames Water. Whenever possible, the network optimization in WATHNET-5 aims to equally distribute the demand shortfall experienced by each demand centre. In reality this is equivalent to water managers ensuring that customer exposure to water shortages is equally shared

among individuals throughout the basin. This equitable risk is achieved under Unlim.R.U, but not in the strategies with smaller transfer volumes that result in little impact on service in the Severn. In addition to this, the probability of severe coincident drought restrictions in the Far Future ensemble under Unlim.R.U are roughly three times less likely than the equivalent measure under Strategy 0 due to the decreased frequency of severe restrictions in the Thames. Indeed, this strategy produces the lowest record of coincident water restrictions across all infrastructure strategies simulated.

These results suggest that transferring upwards of 5000 Ml/d from the Severn to the Thames would be successful in reducing the likelihood of severe water restrictions occurring in Thames Water by 2100. That being said, transferring upwards of 5000 Ml/d will cause unacceptable adverse environmental effects in the River Thames and violate environmental flows in the Severn. The size of the pipeline currently being investigated as part of the feasibility work for the Severn Thames Transfer is <600 Ml/d and is a direct reflection of the environmental effects on the hydro-ecology in the River Thames from imported water. The larger transfers modelled demonstrate the theoretical benefits of high-volume transfers in increasing water supply system resilience to severe meteorological and hydrological droughts, even though they are not appropriate to the real-world Severn-Thames example.

5.5.4 Strategy performance during combined events

The final stage of the drought analysis framework explores the performance of transfer strategies during different types of drought event. ‘Combined drought’ is used to indicate a period when two drought types occur simultaneously. Strategies that prevent water restrictions occurring during a period with a hydrological and/or meteorological drought are preferable over those with little to no improvement in restriction occurrence. **Figure**

5.9 visualises individual time series of SPI, SRI, projected monthly demand, and severe restriction implementation for the Severn and Thames study areas when simulated against one Far Future scenario under Strategies 0, 900.R.U, 900.R.C, 900.R.S and Unlim.R.U. These strategies are illustrated as they provide the largest benefit to Thames Water's risk of restriction, and have the largest impact to Severn Trent's exposure to restrictions. This future scenario is chosen as it contains the highest frequency of severe meteorological and hydrological droughts in both catchments, the highest frequency of severe coincident drought months, and the greatest projected increase in water demand. Note that **Figure 5.9** visualises projected water demand, rather than simulated water demand. This means that decreases in demand as a consequence of water restrictions are not reflected in the time series.

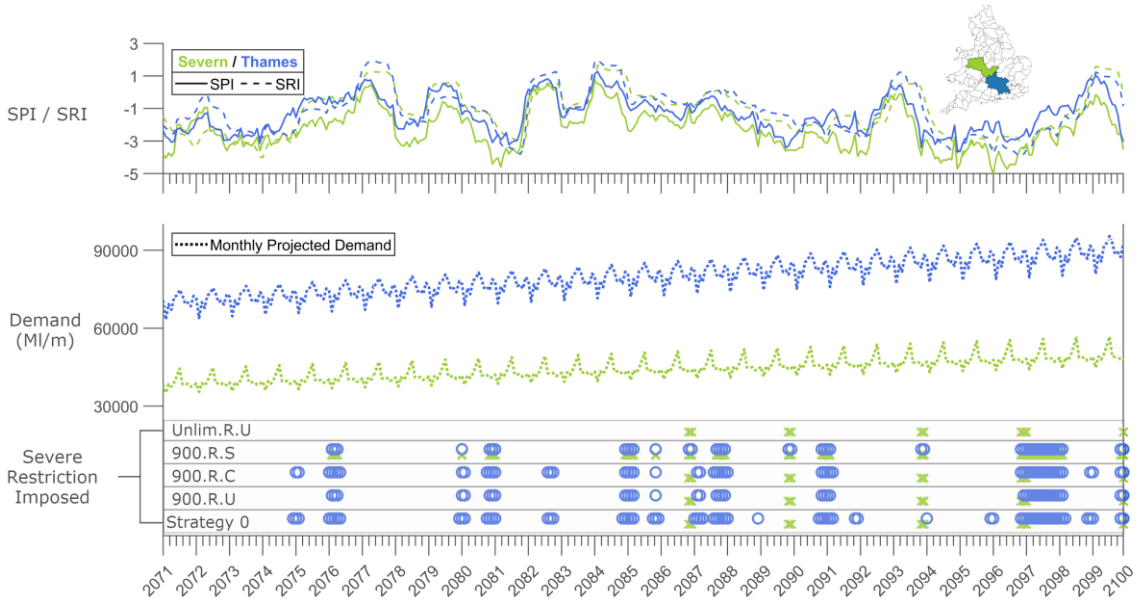


Figure 5.9. Time series of SPI, SRI, projected water demand, and severe restrictions for the Severn (green) and Thames (blue) study areas when simulated under one Far Future scenario with Strategies 0, 900.R.U, 900.R.C, 900.R.S and Unlim.R.U. Each marker represents a severe restriction imposed to Severn Trent (×) or Thames Water (○) customers.

The visualisation further validates the importance of testing different infrastructure strategies against severe spatially coherent drought events. Unsurprisingly, the frequency of restrictions imposed in each water company varies depending on strategy. In the Thames, all transfer strategies improve restriction frequency in 2080, 2086, 2089, 2092 and 2096, compared to Strategy 0. Unlim.R.U, 900.R.U and 900.R.S also reduce drought impact on water supply in 2075, 2082 and 2099. 900.R.S proves the most damaging to service in the Severn, with the largest frequency of restrictions in Severn Trent occurring under this strategy. Restriction frequency consistently increases following sequences of years with decreasing SPI and SRI values, as seen between the years of 2085 and 2088. The frequency of restrictions also increases over time, a consequence of greater demand pressures and recurring drought events that gradually lower water levels in the system over a yearly to decadal timescale. Water planners might consider introducing additional supply infrastructure later in the planning horizon to combat this increase in likelihood of water restrictions.

Complete results from analysis of the probability of combined drought is presented in **Appendix B9**. If a strategy causes a decrease in simultaneous drought occurrence, we infer that strategy increases the resilience of the water supply system to meteorological and/ or hydrological drought. Consistent with the results presented so far, the likelihood of multiple drought types occurring increases into the future for all strategies. This measure is lower in the Severn region, a consequence of the low frequency with which Severn Trent imposes severe restrictions. In the Thames region, water resource drought and hydrological droughts are more likely to coincide than water resource droughts and meteorological droughts, which suggests that hydrological drought events are more closely linked to water restrictions than meteorological droughts. This relationship could be

improved by increasing the time-scale of the meteorological drought (here 12-month SPI) to 18- or 24-months, to better correspond with the hydrological response of the catchment.

Transfer strategies including the Upper Thames reservoir have the greatest influence on the probability of combined drought incidence in the Thames area, improving resilience of the water supply system to meteorological and hydrological drought events. Strategy 300.C showed little or no improvement in resilience. Again, strategies designed to 'share risk' produce higher levels of combined drought occurrence in the Severn region, due to the increased frequency of restrictions and therefore worsened resilience. Overall, the results suggest that the new transfer only increases drought resilience when it has a volume greater than 300Ml/d and is supported by additional infrastructure such as the Upper Thames reservoir which provides extra storage for the transferred water, or the Vyrnwy Redeployment which redirects flows in the Severn to replace water lost to the transfer.

5.6 Discussion and Conclusions

This paper presents a framework for evaluating the resilience of new transfer schemes between neighbouring water companies when simulated against an extended historical record and large ensemble of climate change driven future flows and demand growth projections. The proposed methodology allows water planners to analyse changing characteristics of meteorological and hydrological drought over time and identify adaptation infrastructure that increases the resilience of water supply systems to future drought events.

The approach is applied to a case study in Southern England, using a large ensemble of climate change weather sequences, a library of future flows, demand projections, and simulation-based water resource model. Results show that the probability

and intensity of all drought types increase into the future, but that the magnitude at which the occurrence of drought increases varies between the two study catchments. The analysis also identifies the probability of coincident drought between the neighbouring catchments, revealing how drought dynamics change with time and adaptation. Results indicate that all drought types will become more spatially coherent into the future, with increases in simultaneous severe streamflow and precipitation drought events in both catchments by the mid-21st Century. The results are consistent with previous studies of drought in Southern England, which suggest that major hydrological droughts are more likely to affect multiple catchments into the future (Rudd et al. 2018) and that meteorological drought intensity and stress will likely increase by the 2050s in South East and South West England (Rahiz & New, 2013). Likewise, in the absence of interventions the probability of imposing water restrictions on customers increases throughout the simulation period as water stress increases (Borgomeo et al. 2014). This is more apparent in Thames Water where, in the absence of any of the adaptation actions that Thames Water are planning, the probability of severe water restrictions in any given month in the Far Future may exceed 0.157 (15.7%). The probability of multiple drought events occurring in the same month could also increase into the future, with 18.1% of all months in the Thames study area in the Far Future ensemble simultaneously experiencing a Level 3 or 4 water restriction, severe meteorological drought and severe hydrological drought (without adaptation).

In line with the suggestions made by Watts et al. (2015), to understand how planning decisions are affected by uncertain changes in the climate and hydrological system, this analysis demonstrates the importance of testing competing versions of infrastructure against climate sequences containing drought events of varying spatial coherence and intensity. The analysis differs from previous studies that rely on historical records to test new infrastructure (Kirsch et al. 2013; Palmer & Characklis, 2009; Zeff et

al. 2016), instead comparing the performance of infrastructure simulated under climate change driven scenarios to historical records. Here, the Weather@Home and DECIPHeR ensembles contain more frequent, spatially coherent and intense drought events not present in the historic record, enabling extensive exploration of many possible drought conditions. The ensembles stress test proposed transfer infrastructure between Severn Trent Water and Thames Water, revealing how different management approaches may impact the probability of water restrictions in the transfer source and receiving regions. In general, the most effective strategies include increased storage capacity in the receiving region (Upper Thames reservoir), which provides additional storage for transferred water that can be used in periods of high water stress.

The combined drought analysis explores the probabilities of meteorological and/ or hydrological drought occurring in the same month as water resource drought. The analysis also addresses the role adaptation plays in building resilience to drought. Results indicate that combined drought coincidence decreases in strategies with additional storage capacity, whilst strategies without supporting infrastructure are less successful in building resilience. Unsurprisingly, this suggests that water resource drought resilience to severe climate events improves with greater levels of adaptation. Future strategies should therefore focus on increasing water supply to high risk regions and developing supporting infrastructure to store unused water during periods of low drought risk.

This work also aimed to explore the importance of cooperation between neighbouring companies during drought events, evaluating the trade-off between customer service in the transfer supply region with increased resilience to water restrictions in the receiving region. The results suggest that the new transfer will not increase the exposure of Severn Trent customers to water restrictions, unless it is (i) operated under the ‘shared risk’ agreement which imposes water restrictions to Severn Trent customers whenever

Thames Water customers are charged with a water restriction, or (ii) if the transfer capacity is unfeasibly large. Regarding point (i), the impact of a shared risk policy on restriction frequency in Severn Trent is exaggerated by the modelling framework used here. In simulation, decisions concerning water transfer and allocation are made at every time-step and are informed by present conditions and regulatory constraints. This is a highly simplified version of decision making in the real world, which also uses trend analysis and weather forecasting to inform future decisions about water system operation. The water resource supply model used here therefore lacks important foresight about changing conditions and the risk of future water shortages. A more dynamic representation of water system operation in simulation experiments would provide a better platform to evaluate the complex decision making required to improve cooperation between water companies during periods of heightened drought risk. Regarding point (ii), the low impact observed in Severn Trent in strategies with unconditional and conditional transfer operation is a consequence of the transfer capacities evaluated here, which are not large enough to disrupt service in Severn Trent. In most instances, the reservoirs in the Severn system (Blithfield, Draycote, Clywedog, Carsington and Ogston, Melbourne, Cropston and Thornton) can be drawn from before Elan and Derwent reservoirs are allowed to fall below the thresholds for water restrictions (hence the low number of restrictions imposed in Severn Trent). This is in contrast to the Thames system, which contains no upstream regulatory reservoirs for offline water storage.

The authors acknowledge that multiple factors, other than meteorological and hydrological drought, will influence the success of inter-basin transfers. These factors include, but are not limited to: existing water supply infrastructure, such as reservoir storage volume, pipeline connectivity and levels of leakage; unforeseen changes to spatial and temporal patterns of water consumption; land-use change and altered catchment

characteristics, and; new demand management schemes. For example, Dobson et al. (2020) reveal that the success of water transfers may be dependent on the proximity of reservoir locations between exporting and importing catchments. Results from their UK-based case study indicate a 40% likelihood of reservoirs in neighbouring catchments being in their first percentile of total storage volumes simultaneously, implying that longer distance transfers (>100km) may prove more resilient to drought conditions. The results presented in this study further highlight the importance of exploring different driving forces of large-scale transfer success.

Whilst there is a growing literature on droughts in the UK, few studies have compared different drought types and their changing characteristics throughout the 21st Century. It is hoped that the results from this study will encourage decision makers in the water sector to incorporate multi-dimensional drought analysis in future planning tasks, especially in instances where water resources are shared across basin boundaries and may be vulnerable to changing spatial drought patterns.

5.7 Appendix B: Supplementary materials to Chapter 5

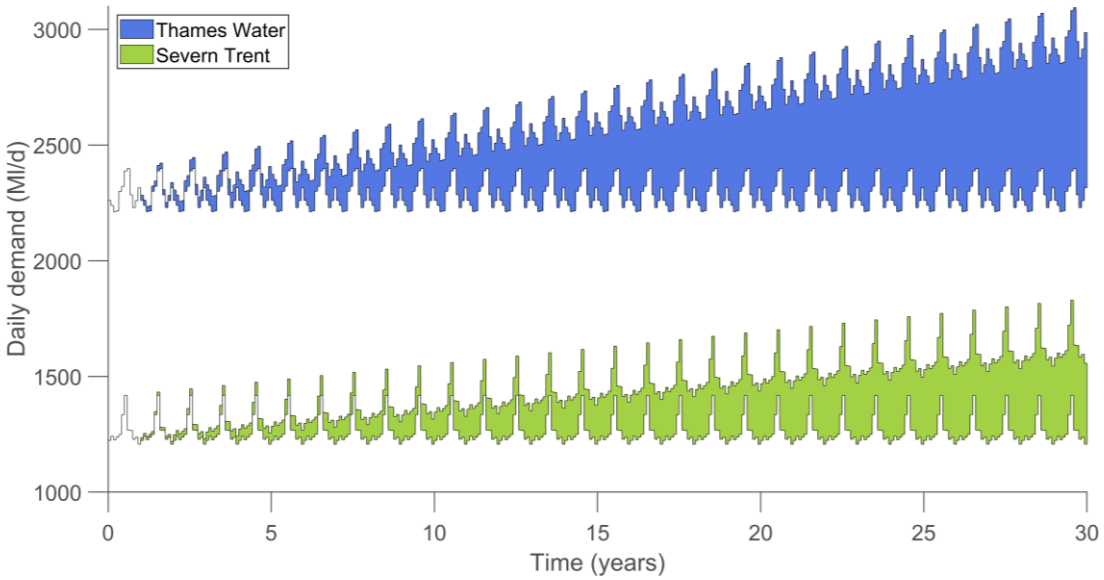
5.7.1 Appendix B1

The DECIPHeR modelling framework uses hydrological response units to simulate the hydrology of similar regions in the landscape. This reduces run time, allowing for simulations of large climate ensembles. For example, one 55-year simulation of flows for 98 river gauges within the Thames Basin (with 8978 hydrological response units) takes roughly 15 minutes to run on a standard CPU.

Supplementary Table 5.1. Performance of DECIPHeR model's ability to capture range of hydrological historical behaviour [from Coxon et al. (2019)].

Evaluation period	**1975-1977**		**1990-1992**		**2002-2004**	
NSE metric	logNSE	NSE	logNSE	NSE	logNSE	NSE
Thames at Teddington (NRFA 39001)	0.86	0.86	0.81	0.80	0.75	0.74
Severn at Saxons Lode (NRFA 54032)	0.89	0.89	0.84	0.85	0.79	0.81

5.7.2 Appendix B2



Supplementary Figure 5.1. 30-year projected demand for the Thames Water and Severn Trent water companies. Demand is aggregated at company level and given in mega-litres per day (ML/d). Intra-annual patterns of demand are a function of water resource zone monthly water demand profiles.

5.7.3 Appendix B3

The Standardized Precipitation Index (SPI) is calculated following the sequence outlined by McKee et al. (1993), using a monthly precipitation time series. The series is formatted to create a set of moving averaging periods that represent different timescales of precipitation deficits. Each monthly value is determined by the precipitation averaged over the previous x months. The dataset of averages is fitted to a Gamma function and the Maximum Likelihood Estimate for the distribution parameters are calculated. A Gamma function is estimated for each catchment and averaging period (month) in the study. The fitted function and parameters are used to calculate the cumulative distribution of the observed precipitation monthly time series. This is then used, with an estimate of the inverse normal, to transform the time series into standardized normal variates. The new values represent the standard deviation from a normally distributed probability density with mean of zero. Standardized Runoff-discharge Index (SRI) is calculated using the same process as SPI.

A one-sample Kolmogorov-Smirnov (KS) test is used to ensure a Gamma distribution is suitable for estimating the drought indices. Kolmogorov-Smirnov tests the hypothesis that the SRI and SPI timescales come from a standard normal distribution. Here the null hypothesis is rejected at the 5% significance level. **Supplementary Table 5.2** presents results from the KS tests for each averaging period (month) in the drought indices time series. A KS-Statistic close to zero indicates the distribution of index values is similar to the normal distribution; a KS-Significance estimate greater than 0.05 implies the alternative hypothesis should be rejected. The results indicate that the null hypotheses for each averaging period in SRI and SPI time series for both study areas cannot be rejected.

Supplementary Table 5.2. KS test results showing the normality of Historic SPI and SRI time series for the Severn and Thames study catchments.

		SPI			SRI		
Catchment	**Averaging period**	**Null hypothesis rejected?**	**Significance**	**KS Statistic**	**Null hypothesis rejected?**	**Significance**	**KS Statistic**
Severn	January	No	0.260	0.137	No	0.380	0.122
Severn	February	No	0.489	0.113	No	0.656	0.098
Severn	March	No	0.248	0.138	No	0.686	0.095
Severn	April	No	0.475	0.114	No	0.594	0.103
Severn	May	No	0.738	0.092	No	0.662	0.097
Severn	June	No	0.627	0.101	No	0.930	0.072
Severn	July	No	0.472	0.114	No	0.945	0.069
Severn	August	No	0.938	0.071	No	0.952	0.068
Severn	September	No	0.668	0.098	No	0.996	0.053
Severn	October	No	0.815	0.085	No	0.437	0.116
Severn	November	No	0.864	0.080	No	0.825	0.083
Severn	December	No	0.730	0.093	No	0.634	0.100
Thames	January	No	0.068	0.177	No	0.596	0.103
Thames	February	No	0.461	0.115	No	0.718	0.093
Thames	March	No	0.139	0.157	No	0.326	0.128
Thames	April	No	0.286	0.133	No	0.313	0.129
Thames	May	No	0.926	0.073	No	0.495	0.111
Thames	June	No	0.690	0.096	No	0.418	0.118
Thames	July	No	0.555	0.107	No	0.377	0.122
Thames	August	No	0.491	0.112	No	0.431	0.117
Thames	September	No	0.158	0.153	No	0.517	0.109
Thames	October	No	0.713	0.094	No	0.463	0.114
Thames	November	No	0.487	0.113	No	0.142	0.155
Thames	December	No	0.255	0.138	No	0.606	0.102

5.7.4 Appendix B4

Supplementary Table 5.3. Probability of month with meteorological drought event of a given severity in one catchment but not the other. For example, row one in the table reveals that the probability of the Severn experiencing a severe meteorological drought in any given month in the Far Future ensemble at the same time as the Thames not experiencing a severe meteorological drought is 0.054, or 5.4%. In contrast, the probability of the Thames catchment experiencing a severe drought whilst the Severn is not in severe drought is 0.47, or 4.7%.

Drought event in Severn	Drought event in Thames	Historic	Baseline	Near Future	Far Future
SPI ≤ Severe	Severe < SPI	0.011	0.020	0.032	0.054
SPI ≤ Moderate	Severe < SPI	0.045	0.059	0.088	0.131
SPI ≤ Mild	Severe < SPI	0.169	0.201	0.264	0.338
SPI ≤ Severe	Moderate < SPI	0.002	0.009	0.014	0.024
SPI ≤ Moderate	Moderate < SPI	0.023	0.034	0.049	0.073
SPI ≤ Mild	Moderate < SPI	0.117	0.157	0.199	0.245
SPI ≤ Severe	Mild < SPI	0.031	0.020	0.025	0.047
SPI ≤ Moderate	Mild < SPI	0.058	0.034	0.041	0.063
SPI ≤ Mild	Mild < SPI	0.082	0.066	0.061	0.076
Severe < SPI	SPI ≤ Severe	0.031	0.020	0.025	0.047
Severe < SPI	SPI ≤ Moderate	0.083	0.059	0.077	0.118
Severe < SPI	SPI ≤ Mild	0.237	0.201	0.236	0.312
Moderate < SPI	SPI ≤ Severe	0.019	0.009	0.010	0.020
Moderate < SPI	SPI ≤ Moderate	0.058	0.034	0.041	0.063
Moderate < SPI	SPI ≤ Mild	0.194	0.157	0.173	0.221
Mild < SPI	SPI ≤ Severe	0.001	0.001	0.001	0.002
Mild < SPI	SPI ≤ Moderate	0.010	0.007	0.006	0.011
Mild < SPI	SPI ≤ Mild	0.082	0.066	0.061	0.076

5.7.5 Appendix B5

Supplementary Table 5.4. Probability of month with hydrological drought event of a given severity in one catchment but not the other. Here, row one in the table reveals that the probability of the Severn experiencing a severe hydrological drought in any given month in the far future ensemble at the same time as the Thames not experiencing a severe hydrological drought is 0.061, or 6.1%. Likewise, the probability of the Thames catchment experiencing a severe drought whilst the Severn is not in severe drought is 0.060, or 6%.

Drought event in Severn	Drought event in Thames	Historic	Baseline	Near Future	Far Future
SRI ≤ Severe	Severe < SRI	0.017	0.025	0.040	0.061
SRI ≤ Moderate	Severe < SRI	0.057	0.064	0.095	0.131
SRI ≤ Mild	Severe < SRI	0.192	0.203	0.277	0.333
SRI ≤ Severe	Moderate < SRI	0.009	0.012	0.016	0.030
SRI ≤ Moderate	Moderate < SRI	0.041	0.039	0.053	0.076
SRI ≤ Mild	Moderate < SRI	0.148	0.161	0.207	0.241
SRI ≤ Severe	Mild < SRI	0.005	0.002	0.003	0.005
SRI ≤ Moderate	Mild < SRI	0.031	0.010	0.013	0.018
SRI ≤ Mild	Mild < SRI	0.101	0.074	0.089	0.099
Severe < SRI	SRI ≤ Severe	0.028	0.025	0.040	0.060
Severe < SRI	SRI ≤ Moderate	0.072	0.062	0.099	0.137
Severe < SRI	SRI ≤ Mild	0.140	0.202	0.270	0.326
Moderate < SRI	SRI ≤ Severe	0.008	0.014	0.020	0.032
Moderate < SRI	SRI ≤ Moderate	0.044	0.039	0.060	0.085
Moderate < SRI	SRI ≤ Mild	0.107	0.160	0.205	0.241
Mild < SRI	SRI ≤ Severe	0.000	0.003	0.005	0.007
Mild < SRI	SRI ≤ Moderate	0.008	0.011	0.017	0.023
Mild < SRI	SRI ≤ Mild	0.033	0.074	0.083	0.095

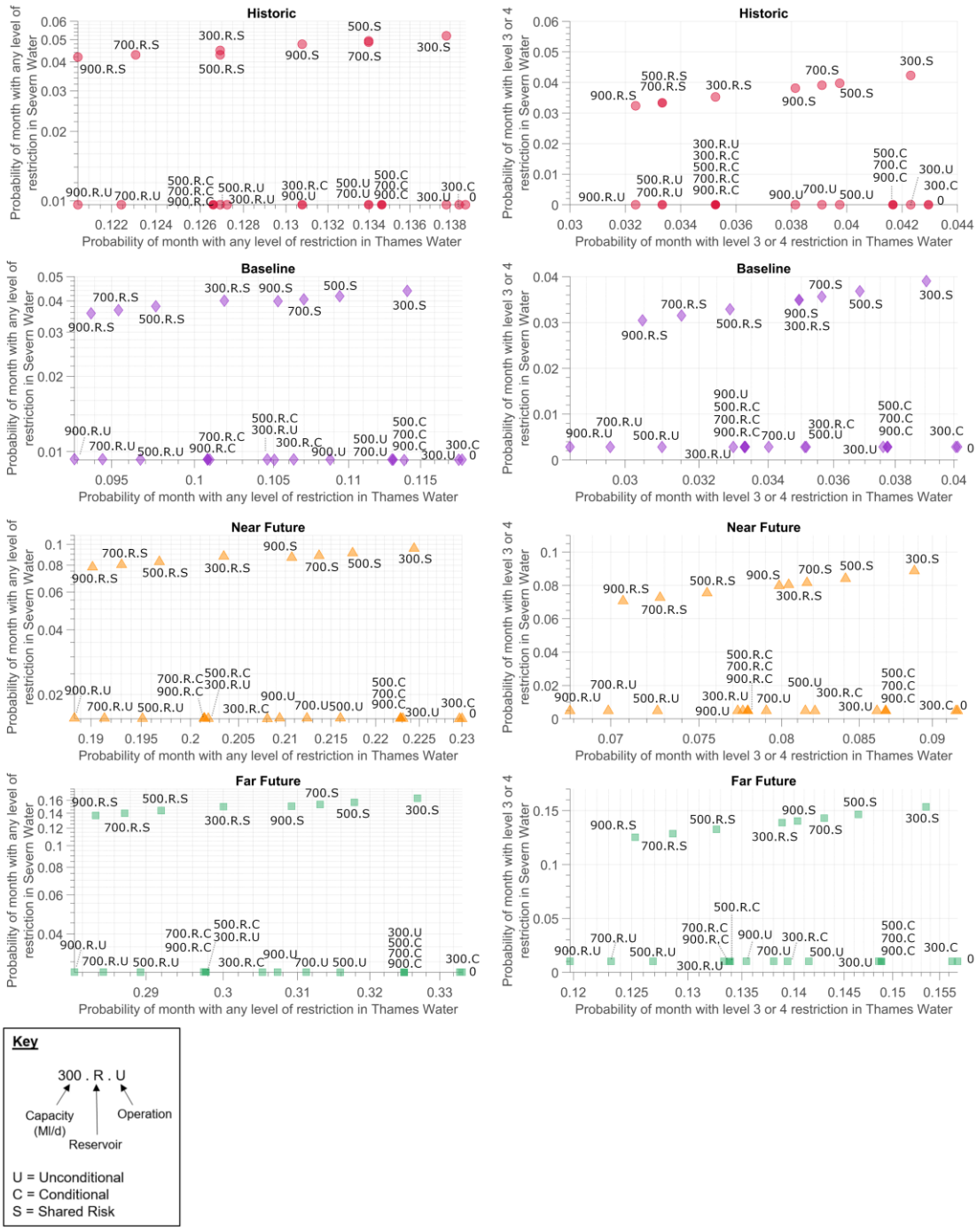
5.7.6 Appendix B6

Supplementary Table 5.5. Probability of Thames and Severn experiencing any level of water restriction (Level 1 to Level 4) in any given month for each infrastructure strategy in Historic, Baseline, Near Future and Far Future.

All restrictions								
Basin	**Severn**				**Thames**			
Strategy Code	**Historic**	**Baseline**	**Near Future**	**Far Future**	**Historic**	**Baseline**	**Near Future**	**Far Future**
0	0.00962	0.00929	0.01544	0.02694	0.13878	0.11798	0.23000	0.33323
300.U	0.00962	0.00926	0.01548	0.02695	0.13782	0.11384	0.22311	0.32484
500.U	0.00962	0.00930	0.01553	0.02688	0.13397	0.10875	0.21605	0.31587
500.R.U	0.00962	0.00930	0.01547	0.02692	0.12692	0.09671	0.19513	0.28931
300.R.U	0.00962	0.00929	0.01547	0.02698	0.12724	0.10094	0.20184	0.29747
300.C	0.00962	0.00928	0.01544	0.02694	0.13846	0.11774	0.22970	0.33291
500.C	0.00962	0.00929	0.01549	0.02687	0.13462	0.11298	0.22287	0.32489
500.R.C	0.00962	0.00931	0.01549	0.02696	0.12660	0.10082	0.20146	0.29775
300.R.C	0.00962	0.00928	0.01543	0.02692	0.13077	0.10506	0.20808	0.30523
300.S	0.05192	0.04388	0.09562	0.16358	0.13782	0.11406	0.22439	0.32676
500.S	0.04936	0.04179	0.09110	0.15667	0.13397	0.10939	0.21741	0.31783
500.R.S	0.04295	0.03807	0.08303	0.14387	0.12692	0.09763	0.19683	0.29195
300.R.S	0.04487	0.04007	0.08792	0.14996	0.12692	0.10186	0.20346	0.30005
700.R.U	0.00962	0.00933	0.01551	0.02698	0.12244	0.09447	0.19134	0.28461
700.R.C	0.00962	0.00931	0.01549	0.02696	0.12660	0.10079	0.20143	0.29774
700.R.S	0.04295	0.03675	0.08036	0.13999	0.12308	0.09540	0.19303	0.28729
700.U	0.00962	0.00931	0.01553	0.02694	0.13397	0.10632	0.21236	0.31117
700.C	0.00962	0.00929	0.01549	0.02687	0.13462	0.11307	0.22285	0.32484
700.S	0.04872	0.04059	0.08861	0.15327	0.13397	0.10699	0.21369	0.31307
900.R.U	0.00962	0.00934	0.01552	0.02697	0.12051	0.09284	0.18840	0.28101
900.R.C	0.00962	0.00931	0.01549	0.02696	0.12660	0.10080	0.20140	0.29771
900.R.S	0.04199	0.03570	0.07834	0.13674	0.12051	0.09380	0.19017	0.28365
900.U	0.00962	0.00931	0.01553	0.02695	0.13077	0.10460	0.20939	0.30727
900.C	0.00962	0.00929	0.01549	0.02687	0.13462	0.11307	0.22283	0.32486
900.S	0.04776	0.03991	0.08686	0.15068	0.13077	0.10529	0.21071	0.30917
Unlim.R.U	0.01474	0.01778	0.02258	0.03089	0.00962	0.00481	0.02320	0.05253

Supplementary Table 5.6. Probability of Thames and Severn experiencing a severe water restriction (Level 3 and Level 4) in any given month for each infrastructure strategy in Historic, Baseline, Near Future and Far Future.

L3 & L4 restrictions								
Basin	**Severn**				**Thames**			
Strategy Code	**Historic**	**Baseline**	**Near Future**	**Far Future**	**Historic**	**Baseline**	**Near Future**	**Far Future**
0	0.00000	0.00287	0.00478	0.01023	0.04295	0.04013	0.09179	0.15694
300.U	0.00000	0.00286	0.00483	0.01031	0.04231	0.03760	0.08619	0.14854
500.U	0.00000	0.00287	0.00483	0.01023	0.03974	0.03515	0.08150	0.14146
500.R.U	0.00000	0.00284	0.00480	0.01022	0.03333	0.03098	0.07260	0.12686
300.R.U	0.00000	0.00284	0.00480	0.01028	0.03526	0.03298	0.07761	0.13331
300.C	0.00000	0.00287	0.00479	0.01027	0.04295	0.04006	0.09168	0.15634
500.C	0.00000	0.00286	0.00478	0.01020	0.04167	0.03773	0.08679	0.14881
500.R.C	0.00000	0.00284	0.00478	0.01020	0.03526	0.03332	0.07792	0.13389
300.R.C	0.00000	0.00285	0.00478	0.01026	0.03526	0.03511	0.08211	0.13937
300.S	0.04231	0.03904	0.08875	0.15353	0.04231	0.03904	0.08875	0.15353
500.S	0.03974	0.03684	0.08410	0.14644	0.03974	0.03684	0.08410	0.14644
500.R.S	0.03333	0.03288	0.07547	0.13261	0.03333	0.03288	0.07547	0.13261
300.R.S	0.03526	0.03493	0.08044	0.13884	0.03526	0.03493	0.08044	0.13884
700.R.U	0.00000	0.00285	0.00481	0.01028	0.03333	0.02961	0.06986	0.12320
700.R.C	0.00000	0.00284	0.00478	0.01021	0.03526	0.03330	0.07791	0.13382
700.R.S	0.03333	0.03152	0.07275	0.12863	0.03333	0.03152	0.07275	0.12863
700.U	0.00000	0.00287	0.00483	0.01029	0.03910	0.03402	0.07905	0.13803
700.C	0.00000	0.00286	0.00478	0.01020	0.04167	0.03774	0.08678	0.14882
700.S	0.03910	0.03563	0.08161	0.14299	0.03910	0.03563	0.08161	0.14299
900.R.U	0.00000	0.00285	0.00481	0.01028	0.03237	0.02859	0.06780	0.11971
900.R.C	0.00000	0.00284	0.00478	0.01021	0.03526	0.03330	0.07790	0.13380
900.R.S	0.03237	0.03046	0.07068	0.12530	0.03237	0.03046	0.07068	0.12530
900.U	0.00000	0.00287	0.00484	0.01031	0.03814	0.03333	0.07730	0.13542
900.C	0.00000	0.00286	0.00478	0.01020	0.04167	0.03775	0.08677	0.14882
900.S	0.03814	0.03493	0.07985	0.14035	0.03814	0.03493	0.07985	0.14035
Unlim.R.U	0.00513	0.01235	0.01325	0.01486	0.00000	0.00072	0.00541	0.01508



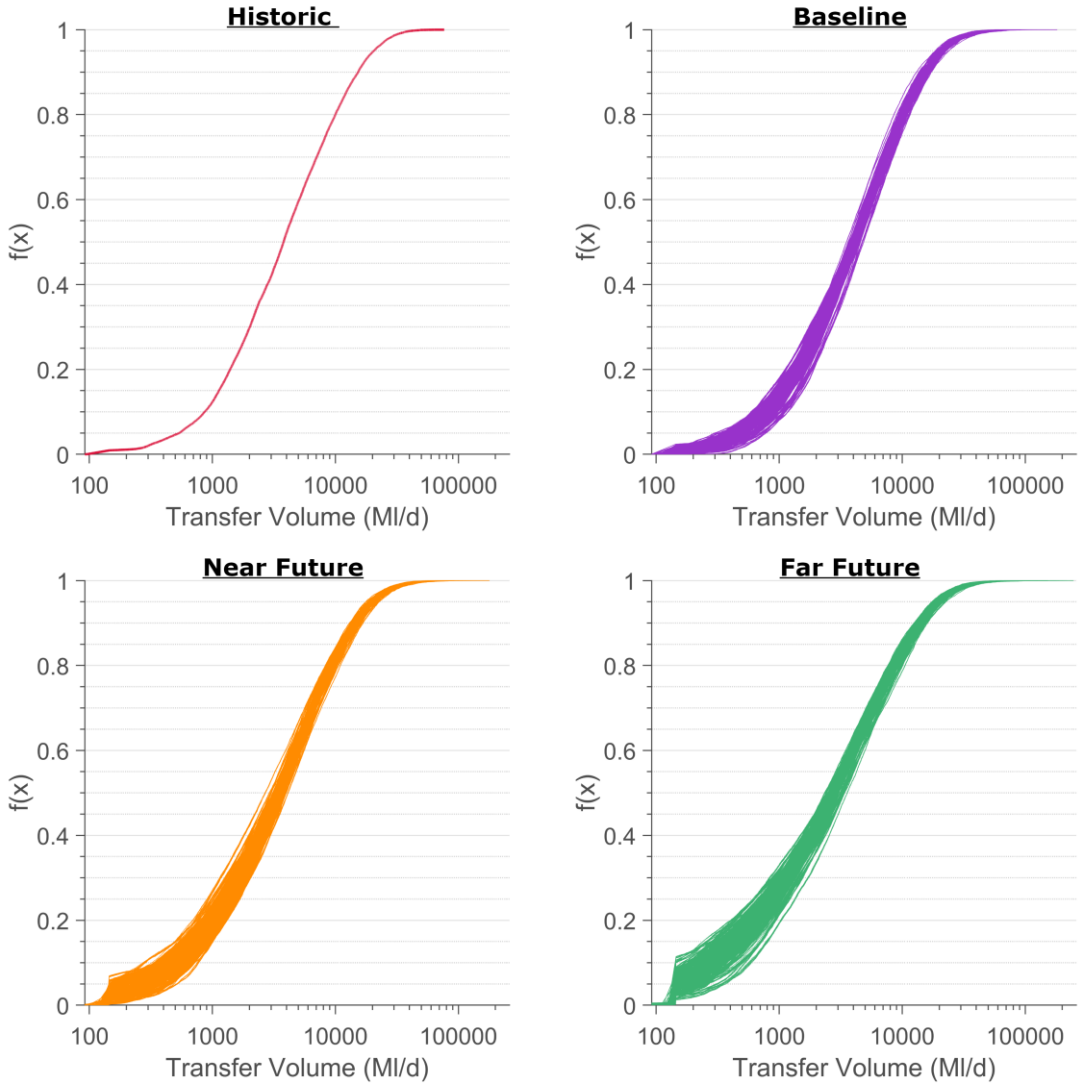
Supplementary Figure 5.2. Probability of Thames and Severn experiencing any level of water restriction (left column) and severe / Level 3 and Level 4 water restrictions (right column) in any given month for each infrastructure strategy. Note the unlimited strategy (Unlim.R.U) is not plotted.

5.7.7 Appendix B7

Supplementary Table 5.7. Probability of Thames and Severn water resource regions experiencing any level (Level 1 to Level 4) of water restrictions and severe water restrictions (Level 3 and Level 4) simultaneously in any given month in the simulation (to 5 s.d.).

Restriction level	**All restrictions**				**L3 & L4 restrictions**			
Strategy Code	**Historic**	**Baseline**	**Near Future**	**Far Future**	**Historic**	**Baseline**	**Near Future**	**Far Future**
0	0.00064	0.00559	0.01067	0.01938	0.00000	0.00100	0.00185	0.00463
300.U	0.00064	0.00555	0.01062	0.01928	0.00000	0.00098	0.00190	0.00464
500.U	0.00064	0.00547	0.01054	0.01910	0.00000	0.00098	0.00189	0.00451
500.R.U	0.00064	0.00475	0.00934	0.01746	0.00000	0.00074	0.00159	0.00380
300.R.U	0.00064	0.00479	0.00944	0.01764	0.00000	0.00075	0.00162	0.00389
300.C	0.00064	0.00558	0.01067	0.01938	0.00000	0.00100	0.00186	0.00466
500.C	0.00064	0.00552	0.01062	0.01918	0.00000	0.00098	0.00183	0.00451
500.R.C	0.00064	0.00479	0.00942	0.01761	0.00000	0.00075	0.00158	0.00382
300.R.C	0.00064	0.00482	0.00949	0.01767	0.00000	0.00077	0.00160	0.00389
300.S	0.04295	0.04108	0.09240	0.15842	0.04231	0.03904	0.08875	0.15353
500.S	0.04038	0.03890	0.08775	0.15142	0.03974	0.03684	0.08410	0.14644
500.R.S	0.03397	0.03470	0.07896	0.13758	0.03333	0.03288	0.07547	0.13261
300.R.S	0.03590	0.03673	0.08392	0.14376	0.03526	0.03493	0.08044	0.13884
700.R.U	0.00064	0.00470	0.00929	0.01742	0.00000	0.00073	0.00158	0.00385
700.R.C	0.00064	0.00480	0.00939	0.01760	0.00000	0.00075	0.00158	0.00382
700.R.S	0.03397	0.03330	0.07621	0.13363	0.03333	0.03152	0.07275	0.12863
700.U	0.00064	0.00546	0.01051	0.01912	0.00000	0.00097	0.00188	0.00457
700.C	0.00064	0.00552	0.01062	0.01918	0.00000	0.00098	0.00183	0.00451
700.S	0.03974	0.03768	0.08523	0.14799	0.03910	0.03563	0.08161	0.14299
900.R.U	0.00064	0.00467	0.00928	0.01737	0.00000	0.00073	0.00158	0.00384
900.R.C	0.00064	0.00480	0.00939	0.01759	0.00000	0.00075	0.00158	0.00382
900.R.S	0.03301	0.03221	0.07416	0.13034	0.03237	0.03046	0.07068	0.12530
900.U	0.00064	0.00542	0.01044	0.01907	0.00000	0.00097	0.00188	0.00458
900.C	0.00064	0.00552	0.01062	0.01918	0.00000	0.00098	0.00183	0.00451
900.S	0.03878	0.03696	0.08345	0.14535	0.03814	0.03493	0.07985	0.14035
Unlim.R.U	0.00000	0.00066	0.00209	0.00690	0.00000	0.00022	0.00048	0.00160

5.7.8 Appendix B8



Supplementary Figure 5.3. Empirical cumulative distribution function of volume of water transferred in simulations of strategy Unlim.R.U under Historic, Baseline, Near Future and Far Future ensembles. Each line plotted represents an individual scenario. Note: volumes equal to zero (days when no water is transferred) are omitted on the graph; a consequence of the logarithmic scale on the x-axis.

5.7.9 Appendix B9

Supplementary Table 5.8. Probability of extreme meteorological, hydrological and water resource drought months occurring simultaneously in individual regions (to 5 s.d.).

M = Meteorological drought, H = Hydrological drought, RS = Severe Water Restrictions

L3 & L4 restrictions						
Drought type	**M-RS**		**H-RS**		**M-H-RS**	
Region	**S**	**T**	**S**	**T**	**S**	**T**
Strategy Code	**Baseline**					
0	0.00080	0.01930	0.00080	0.02660	0.00013	0.00813
300.U	0.00080	0.01800	0.00080	0.02453	0.00013	0.00763
500.U	0.00080	0.01610	0.00077	0.02180	0.00013	0.00667
500.R.U	0.00080	0.01353	0.00077	0.02020	0.00013	0.00610
300.R.U	0.00080	0.01473	0.00077	0.02183	0.00013	0.00683
300.C	0.00080	0.01927	0.00080	0.02667	0.00013	0.00817
500.C	0.00080	0.01757	0.00077	0.02440	0.00013	0.00763
500.R.C	0.00080	0.01433	0.00077	0.02197	0.00013	0.00650
300.R.C	0.00080	0.01550	0.00080	0.02317	0.00013	0.00713
300.S	0.02150	0.01847	0.01883	0.02600	0.01087	0.00760
500.S	0.01987	0.01667	0.01680	0.02333	0.00957	0.00667
500.R.S	0.01787	0.01423	0.01527	0.02170	0.00863	0.00603
300.R.S	0.01907	0.01540	0.01627	0.02330	0.00957	0.00673
700.R.U	0.00080	0.01220	0.00080	0.01883	0.00013	0.00553
700.R.C	0.00080	0.01757	0.00077	0.02440	0.00013	0.00763
700.R.S	0.01653	0.01623	0.01420	0.02223	0.00767	0.00640
700.U	0.00080	0.01183	0.00080	0.01843	0.00013	0.00537
700.C	0.00080	0.01433	0.00077	0.02193	0.00013	0.00650
700.S	0.01940	0.01250	0.01633	0.02003	0.00920	0.00533
900.R.U	0.00080	0.01517	0.00080	0.02040	0.00013	0.00637
900.R.C	0.00080	0.01757	0.00077	0.02440	0.00013	0.00763
900.R.S	0.01583	0.01567	0.01397	0.02197	0.00743	0.00630
900.U	0.00080	0.00000	0.00080	0.00037	0.00013	0.00000
900.C	0.00080	0.01433	0.00077	0.02193	0.00013	0.00650
900.S	0.01883	0.01290	0.01620	0.02040	0.00913	0.00550
Unlim.R.U	0.00653	0.01573	0.00573	0.02067	0.00273	0.00643
Strategy Code	**Near Future**					
0	0.00466	0.11328	0.00466	0.14164	0.00144	0.05474
300.U	0.00466	0.10603	0.00466	0.13454	0.00144	0.05184
500.U	0.00466	0.10060	0.00466	0.12897	0.00144	0.04899
500.R.U	0.00463	0.09132	0.00466	0.11724	0.00144	0.04471
300.R.U	0.00463	0.09736	0.00466	0.12454	0.00144	0.04822
300.C	0.00466	0.11322	0.00466	0.14124	0.00144	0.05471
500.C	0.00466	0.10704	0.00466	0.13543	0.00144	0.05216
500.R.C	0.00466	0.09756	0.00466	0.12368	0.00144	0.04810
300.R.C	0.00463	0.10313	0.00466	0.12948	0.00144	0.05078
300.S	0.11603	0.10836	0.12443	0.13911	0.07270	0.05216
500.S	0.11149	0.10270	0.12020	0.13368	0.07052	0.04911
500.R.S	0.10121	0.09391	0.10934	0.12241	0.06388	0.04506
300.R.S	0.10724	0.10006	0.11506	0.12963	0.06764	0.04862
700.R.U	0.00468	0.08782	0.00466	0.11394	0.00144	0.04319
700.R.C	0.00466	0.10707	0.00466	0.13537	0.00144	0.05218

Supplementary Table 5.8. Continued

L3 & L4 restrictions						
Drought type	**M-RS**		**H-RS**		**M-H-RS**	
Region	**S**	**T**	**S**	**T**	**S**	**T**
Strategy Code	**Near Future**					
700.R.S	0.09793	0.09925	0.10603	0.13078	0.06218	0.04747
700.U	0.00466	0.08606	0.00466	0.11138	0.00144	0.04213
700.C	0.00466	0.09756	0.00466	0.12374	0.00144	0.04813
700.S	0.10848	0.08885	0.11761	0.11644	0.06868	0.04250
900.R.U	0.00468	0.09503	0.00466	0.12411	0.00144	0.04644
900.R.C	0.00466	0.10707	0.00466	0.13534	0.00144	0.05218
900.R.S	0.09595	0.09736	0.10411	0.12891	0.06103	0.04667
900.U	0.00466	0.00603	0.00466	0.01353	0.00144	0.00244
900.C	0.00466	0.09759	0.00466	0.12371	0.00144	0.04810
900.S	0.10652	0.09055	0.11598	0.11894	0.06759	0.04351
Unlim.R.U	0.01276	0.09716	0.01609	0.12609	0.00586	0.04730
Strategy Code	**Far Future**					
0	0.02460	0.30451	0.01879	0.33908	0.01247	0.18149
300.U	0.02460	0.28908	0.01894	0.32290	0.01247	0.17328
500.U	0.02414	0.27598	0.01853	0.30730	0.01218	0.16563
500.R.U	0.02414	0.25034	0.01853	0.27534	0.01218	0.15195
300.R.U	0.02460	0.26299	0.01885	0.28865	0.01247	0.15905
300.C	0.02460	0.30325	0.01894	0.33805	0.01247	0.18089
500.C	0.02414	0.28888	0.01851	0.32247	0.01218	0.17276
500.R.C	0.02414	0.26448	0.01853	0.28908	0.01218	0.15899
300.R.C	0.02460	0.27474	0.01888	0.30109	0.01247	0.16549
300.S	0.31770	0.30126	0.32583	0.33428	0.21046	0.17851
500.S	0.30382	0.28787	0.31213	0.31876	0.20167	0.17052
500.R.S	0.28175	0.26440	0.28540	0.28851	0.18799	0.15805
300.R.S	0.29382	0.27687	0.29825	0.30124	0.19655	0.16494
700.R.U	0.02414	0.24428	0.01853	0.26885	0.01218	0.14920
700.R.C	0.02414	0.28885	0.01853	0.32244	0.01218	0.17273
700.R.S	0.27511	0.28040	0.27899	0.31126	0.18356	0.16635
700.U	0.02414	0.23830	0.01853	0.26172	0.01218	0.14580
700.C	0.02414	0.26425	0.01851	0.28879	0.01218	0.15891
700.S	0.29713	0.25270	0.30520	0.27474	0.19635	0.15184
900.R.U	0.02414	0.26233	0.01853	0.29402	0.01218	0.15802
900.R.C	0.02414	0.28882	0.01853	0.32241	0.01218	0.17270
900.R.S	0.26868	0.27448	0.27305	0.30477	0.17922	0.16284
900.U	0.02425	0.03730	0.01853	0.03681	0.01218	0.02425
900.C	0.02414	0.26437	0.01851	0.28897	0.01218	0.15894
900.S	0.29101	0.25767	0.29908	0.28109	0.19256	0.15468
Unlim.R.U	0.03333	0.26871	0.02822	0.30066	0.01782	0.16181

6 Regulation of freshwater use to restore ecosystem resilience

Abstract

Concern about the impacts of water regulation upon the aquatic environment has led to increasingly stringent regulatory constraints on the quantity and timing of freshwater withdrawals. For the time being these regulatory constraints tend to be articulated in terms of limits upon withdrawals, partly because of limited knowledge of the condition and resilience of the aquatic ecosystems. A more sophisticated approach to regulation would be more directly related to indicators of ecological condition. Moreover, it would consider ecosystem response to climatic events not present in the historical record. In this paper we use a combination of empirical evidence of ecosystem condition with simulation to propose and test reductions to regulatory limits on river water withdrawals and downstream minimum flow requirements. The study uses multi-level linear regression to relate existing macroinvertebrate indices to antecedent flow statistics over a period of historical observations. The derived model is used to forecast the response of macroinvertebrate indices to future flow scenarios and demand forecasts, incorporating the uncertainties in ecosystem response. Simulation is used to evaluate the sensitivity of the indices to different regulatory limits. The framework demonstrates how regulation could move from precautionary limits on withdrawals to an approach based on observations, forecasting and simulation, allowing planners to refine the trade-offs between river health and reliable water supply in the face of uncertainty.

6.1 Introduction

There is mounting evidence that hydrological alteration and riverine habitat degradation influence river ecosystems (WWF, 2018), with growing demand for water threatening 65% of river habitats (Vörösmarty et al. 2010). Globally, increased water withdrawals throughout the 20th and early 21st Century have left rivers fragmented (Biemans et al. 2011) and with reduced flows (Richter et al. 2003). In England, water withdrawal for public water supply has had a damaging effect on ecosystems, with an estimated 20% of rivers suffering from over-abstraction (Environment Agency, 2019a). Increased risk of ecosystem damage has led to 'opinion' driven implementation of precautionary regulatory thresholds (Klaar et al. 2014), which typically set limits and restrict the removal of water during periods of low flow. Whilst such schemes aim to sustain riverine ecosystems (Poff & Zimmerman, 2010), they fail to reflect the dynamism of ecosystems under shifting environmental regimes (Arthington et al. 2018). Moreover, very little has been done to explore the relationship of regulatory limits on water withdrawals to climatological, hydrological and demand side uncertainties inherent in water systems planning. For these reasons, practitioners and researchers alike have called for: (i) improvements in methodology to inform and support water management decisions (Stoffels et al. 2018); (ii) development of rigorous predictive science frameworks (Poff, 2018); and, (iii) recognition of risk in riverine management (Acreman et al. 2014).

To minimise the environmental impact of water withdrawals, it is imperative to understand the interaction between management decisions and riverine ecosystems. Traditional hydro-ecological studies have shown that different elements of the flow regime influence biotic community in river habitats (Acreman et al. 2014; Bunn & Arthington, 2002). Hydro-ecological relationships can be characterised using statistical associations between antecedent flow and macroinvertebrate indices (Monk et al. 2007; Monk et al.

2006); relationships which are then used to prescribe environmental flow thresholds for river reaches. Multi-level regression models (Dunbar et al. 2010), Principle Component Analysis (Clews & Ormerod, 2009; Worrall et al. 2014), ANOVA (Clews & Ormerod, 2010), and Generalized Linear Mixed Effects Models (England et al. 2019) have all been used to explore biotic responses to environmental change. These tools have proved successful in motivating decision makers (Kendy et al. 2012), with planners aiming to minimise flow alterations from the natural river condition (Olivares et al. 2015), or target flows to achieve specific ecological outcomes (Barbour et al. 2016; Basdekas et al. 2014).

Biomonitoring tools are commonly used within environmental flow studies to explore biotic response to changing abiotic conditions in river environments. As Mellado-Díaz et al. (2019) conclude in their study of longitudinal trends and recovery gradients of macroinvertebrate (MI) indices along regulated rivers, biomonitoring tools can provide key information for water managers, environmental authorities, and other practitioners. Macroinvertebrate indices such as Lotic Invertebrate index for Flow Evaluation (LIFE), Biological Monitoring Working Party score (BMWP), Whalley Hawkes Paisley Trigg metric (WHPT), and Proportion of Sediment-sensitive Invertebrates index (PSI) have been used frequently to investigate historical change in river habitats. Mathers et al. (2016) use a multi-metric approach (LIFE, PSI, BMWP and more) to evaluate the impact of invasive freshwater crayfish on macroinvertebrates, whilst Clews & Ormerod (2010) use BMWP to explore effects of riparian management on stream biota. Both Chadd et al. (2017) and England et al. (2019) have recently developed indices to asses macroinvertebrate responses to drought effect on habitat loss (DEHLI-index), and environmental changes in river flowing, ponded and drying states (MIS-index), respectively. Each study found that antecedent low flows exhibited strong negative relationships with the indices, suggesting that lower than average flows contributed to a worsened macroinvertebrate score. Their

findings support the earlier study by Dunbar et al. (2010), which uses flow statistics and local-scale habitat features to predict LIFE scores in catchments in England and Denmark.

Macroinvertebrate indices have also been used to examine the impact of infrastructure and other human interventions on past river health. Krajenbrink et al. (2019) use a multi-scale experiment to investigate the impact of water supply reservoirs on macroinvertebrate communities in England, revealing historic long-term changes in instream communities as a consequence of impoundment. Elsewhere, Westwood et al. (2017) use macrophytes and macroinvertebrate observations to assess the impact of aquifer depletion on river community composition in the Thames Basin. Over-abstraction of groundwater is shown to have negatively impacted ecosystem health over time, with results from the study illustrating the importance of careful management of environmental flow thresholds.

Despite the density of studies investigating macroinvertebrate response to hydrological change, very few assess the impact of climate change and increased water demand on macroinvertebrate assemblages and river health. The studies discussed thus far base environmental management decisions on historically observed trends, thus failing to consider future drivers of change that are not represented in existing records. Whilst several studies have touched on the importance of climate non-stationarity, extreme events, historically observed warming and land use stressors on metrics of river health (Murdoch et al. 2020; Thompson et al. 2018), these studies do not examine future projections of change. Visser et al. (2019) present one of the few studies that quantifies hydro-ecological response to 21st Century climate change. Their coupled hydrological-ecological framework uses weather sequences from the UKCP09 climate projections for the UK to examine patterns in functional composition of macroinvertebrate community under a high emissions scenario. Results indicate that a shift away from baseline conditions

and decreased inter-annual variability in flow are likely to impact the structure of macroinvertebrate communities and ecosystem functionality.

Much like the work by Visser et al. (2019), this study presents a climate-hydro-ecological response framework. Unlike previous studies however, we couple simulation and hydro-ecological modelling to examine macroinvertebrate response to different water system management strategies and future drivers of change. Water system simulation has been used widely in water planning, to examine water resource investment portfolios (Borgomeo et al. 2018), investigate river water quality (Bussi et al. 2016; Mortazavi-Naeini et al. 2019), and explore cooperative transboundary management (Wheeler et al. 2018). Yet few studies have used simulation for the purpose presented here. The proposed joint assessment of river health and water resource planning combines aspects of two paradigms that have traditionally remained separate: environmental flow assessment and risk-based water resource planning. The case study application provides a working example of how the environmental impact of strategic water planning can be tested against future scenarios and associated uncertainties, and how regulation can be moderated through the exploration of emerging trade-offs between water supply and environmental degradation.

6.2 Data and methods

This section presents a simulation-based framework to inform future water system planning (**Figure 6.1**). The workflow is divided into three sections: (i) statistical hydro-ecological model development using historical flow observations and macroinvertebrate indices; (ii) water resource simulation of regulation strategies under historical and uncertain future scenarios; and, (iii) evaluation of simulated water supply system and macroinvertebrate community response to different management strategies throughout

the 21st Century. The framework is designed to evaluate regulation strategies against a wide range of uncertain scenarios, and in doing so explore the trade-offs between river health and reliable water supply. The framework is applied to the River Lee catchment in South East England, which is part of the wider Thames Basin and a public water supply source for London.

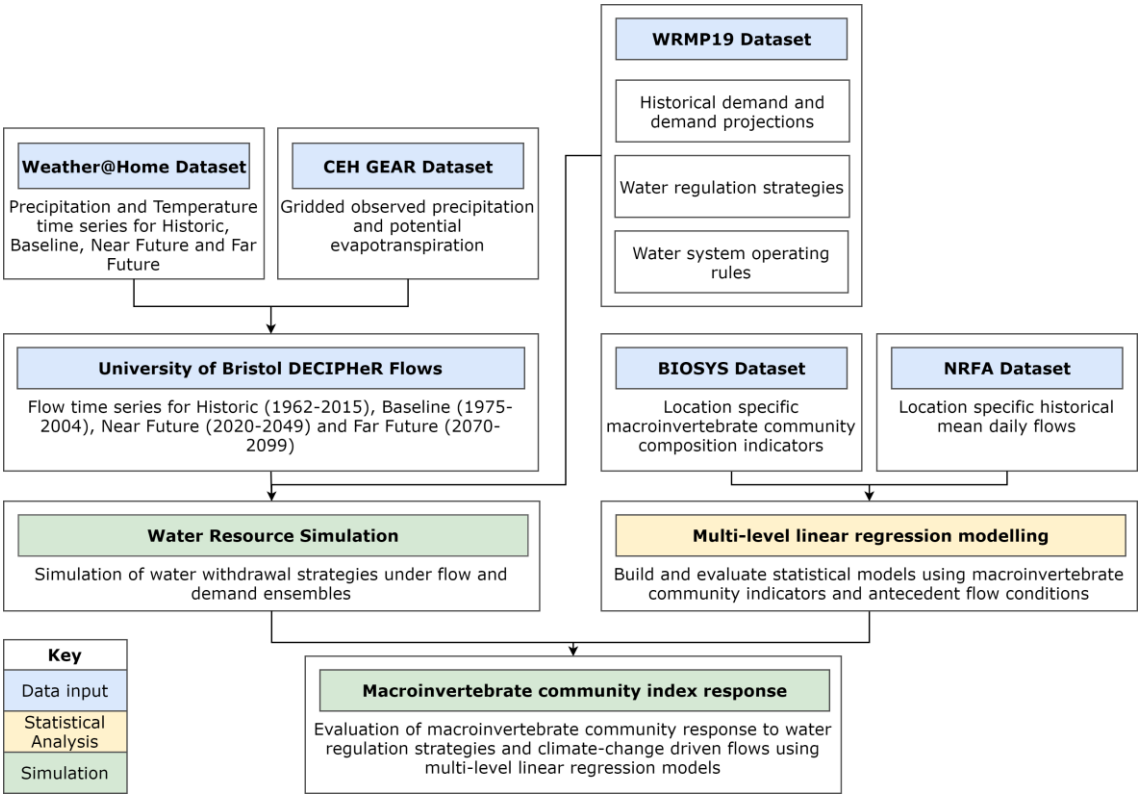


Figure 6.1. Flowchart of the simulation and hydro-ecological modelling framework.

6.2.1 Study area

The River Lee is chosen to demonstrate the utility of the modelling framework. The River Lee catchment covers an area of 1385km^2, overlays limestone (chalk) geology and flows into the River Thames from North East London (NERC CEH Wallingford, 2018). The water utility Thames Water abstracts water directly from the Lee, supplying customers in Hornsey, Coppermills and the wider London water resource zone. Within the lower Lee Valley, Thames Water operate a sequence of offline raw water storage reservoirs that are

principally fed by withdrawals from the Lee. Hydrology along the lower river reach is influenced by surface water withdrawals and discharges from sewage treatment works adjacent to the Lee reservoirs (Mulder et al. 2018).

As part of a national initiative to improve environmental conditions along rivers, the English Environment Agency requires water companies to reduce surface water withdrawals (where feasible) and improve efforts to increase flows in rivers (Environment Agency, 2019a; Thames Water, 2019a). Reductions in surface water withdrawals are often fixed in time and defined according to what would be an acceptable level of withdrawal under historical trends. The framework presented here enables simulation of withdrawal licence reduction schemes and flow regulation policies against future climate and demand scenarios, whilst simultaneously evaluating the benefit of increased downstream flows on ecosystem health.

6.2.2 System model

Figure 6.2 presents a simplified schematic of the Lee Valley water system to be modelled. Here, the system is represented by a series of nodes and arcs in the network flow model, WATHNET-5 (Kuczera, 1992). This model has previously been used to simulate long term water resource planning portfolios in the Thames Basin against climate change uncertainty (Borgomeo et al. 2018; Hall et al. 2019). Within WATHNET-5, arcs represent flow pathways (rivers and pipes) that connect inflow, groundwater, reservoir, demand and waste nodes. Flow arcs are assigned individual costs, which prioritise allocation of flow through an arc. Environmental flow arcs are given a negative cost to ensure that the minimum required flow (MRF) is met. In the Lee Valley system model, the current MRF for Arc M is set at 45 mega-litres per day (Ml/d), based on regulatory requirements for that reach.

In this study, the Lee water supply network is nested within a larger model of the Thames water system. This approach provides more accurate boundary conditions for the individual water network (Dobson et al. 2019), ensuring that water supply allocation within the Lee Valley represents real life management of the Thames system and the interconnected nature of the London water supply grid. Note that multiple inflow and demand nodes in the Thames system model are not represented in **Figure 6.2**. The larger system model contains nine demand nodes, twelve surface water nodes, and seven groundwater nodes. Within the system model, the Lee Valley reservoirs are aggregated into one large reservoir node and can directly pump withdrawals from the river. The demand (London Demand Centre) and waste node (Thames Estuary) act as sinks in the network. Here the London Demand Centre represents demand of water users in the London water resource zone.

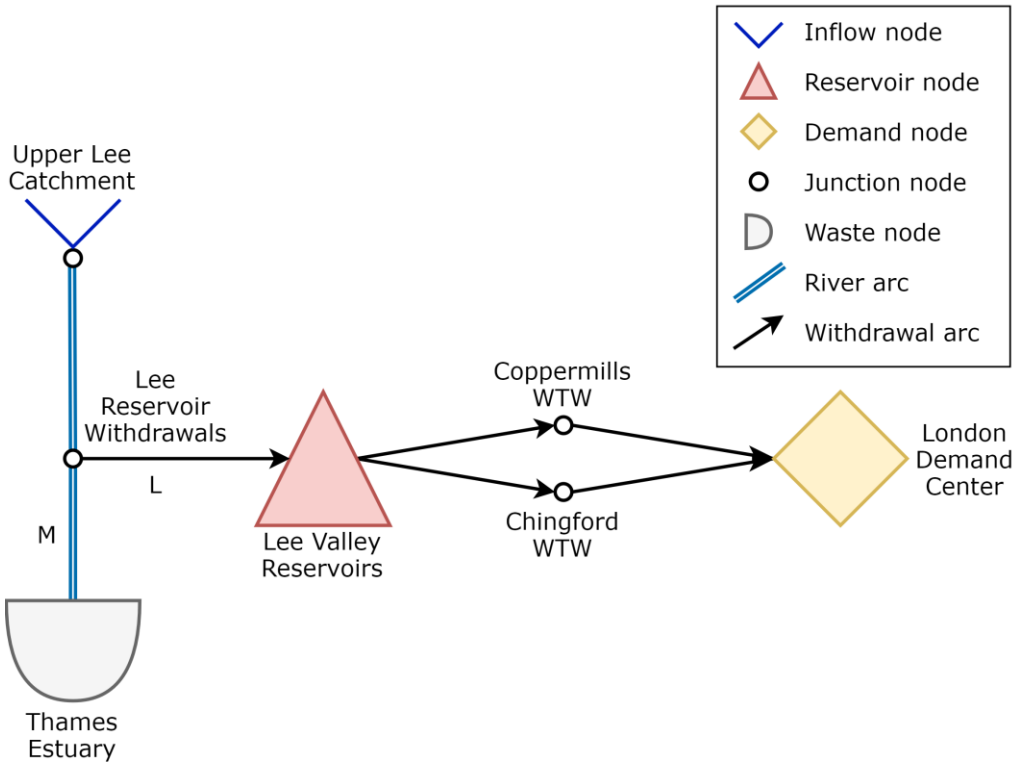


Figure 6.2. Water resource system model schematic.

6.2.2.1 Model inputs

Flows are input into the system model via inflow nodes. This study uses a coupled climatological-hydrological modelling framework to generate flows for the Lee catchment and other inflow nodes in the larger Thames water system model. Historically observed and emissions-driven precipitation (P) and evapotranspiration (PET) time series from the CEH GEAR (Tanguy et al. 2019) and Weather@Home (W@H) platform (Guillod et al. 2017), respectively, are used to run the DECIPHeR (Dynamic fluxEs and ConnectIvity for Predictions of HydRology) hydrological model, developed by Coxon et al. (2019).

Weather@Home weather sequences are generated using a Global Circulation Model (HadAM3P) downscaled with the Met Office Regional Climate Model, HadRM3p, and driven with historic (HadISST) and projected (CMIP5) sea surface temperatures (SST) and sea ice. A complete description of the climate modelling process, bias correction, and validation is presented in Guillod et al. (2017, 2018). Modelled W@H P and PET for the Lee and other Thames Basin catchments are simulated for three time periods. In the Baseline period (1975-2004), 100 realisations were generated using different initial atmospheric conditions, and historic SST and sea ice records from HadISST (Rayner et al. 2003; Titchner & Rayner, 2014). In the Near Future period (2020-2049), 100 realisations were generated using 50th percentile SST and sea ice projections (CMIP5, (Taylor et al. 2012)) under Representative Concentration Pathway 8.5 (Meinshausen et al. 2011). 100 realisations are generated for the Far Future period (2070-2099) using 50th percentile SST and sea ice projections under RCP8.5.

The DECIPHeR modelling framework consists of sub-catchment-based hydrological response units (HRUs) that group hydrologically similar areas according to landscape attributes and spatial variability of climatic inputs. Previous work has shown that DECIPHeR achieves good model performance across 1366 flow locations in the UK

when evaluated against historically observed flows, with 92% of simulations using 10,000 model parameter sets achieving a Nash-Sutcliffe efficiency score greater than zero (Coxon et al. 2019). The best DECIPHeR parameter sets, according to NSE and logNSE scores, were identified for 338 catchments in England and Wales by Dobson et al. (2020) in their analysis of 21st Century droughts. Following the same hydrological modelling framework outlined by Dobson et al. (2020), this study uses the best DECIPHeR parameter sets for catchments in the Thames Basin to simulate hydro-meteorological flow conditions at a 5km resolution. **Appendix C1** lists the NSE and logNSE of the calibrated historic DECIPHeR flows for the Thames at Teddington (NRFA station 39001) and Lee at Feildes Weir (NRFA station 38001). The water system model (**Figure 6.2**) uses DECIPHeR flow sequences for the CEH GEAR Historic period (1962-2015), and flow sequences for the W@H Baseline, Near Future and Far Future periods. Plots of the empirical cumulative distribution functions (ecdfs) for simulated flows and corresponding flow statistics for the Upper Lee catchment are presented in **Appendix C2**. 9000 years of W@H modelled daily flows are available for each inflow node in the system model. Groundwater inflows are set at the licenced withdrawal limit, defined by the Environment Agency (Environment Agency, 2013b).

Historic demand is estimated using dry year annual average distribution input at water resource zone level and annual demand profiles, and paired with the Historic CEH GEAR-DECIPHeR flow scenario. Ten scenarios of future municipal water demand are estimated using dry year annual average distribution input and demand profiles, and scaled according to Thames Water water resource planning tables (Environment Agency, 2019b; Thames Water, 2019a). Each future demand scenario is coupled with the 100 Baseline, Near Future and Far Future W@H-DECIPHeR flow scenarios, to create a library of 3000 scenarios (total of 90,000 simulation years). WATHNET-5 is used to simulate the water

system under the historical conditions and 3000 W@H climate and demand scenarios. Simulation output can include, but is not limited to, demand deficits, river flows, minimum required flow violations, and frequency of water restrictions imposed on customers. This study uses simulated daily flow volume along Arc M and simulated daily withdrawals along Arc L (**Figure 6.2**).

6.2.2.2 Water withdrawal strategies

Water is abstracted from the river at the Lee Reservoir Withdrawals point along Arc L in **Figure 6.2**. A 'no change' system model is first run under the Historic flow and water demand scenario using the current daily abstraction licence of 1200 Ml/d (Environment Agency, 2013). The simulated water withdrawals over the Historic period (1962-2015) are used to identify water withdrawal strategies to be simulated under the future flow and demand scenarios (**Table 6.1**). The strategies examined introduce proportional reductions to the simulated daily water withdrawals over the Historic period. The system model is also used to explore the impact of altered downstream minimum flow requirements on river health, by simulating regulation policies with different MRF limits along Arc M. The existing MRF along Arc M (45Ml/d) is equivalent to the 95th percentile (Q95) of historical (1900-2000) daily mean flows recorded at NRFA gauging station 38001, located above the Lee Reservoir Withdrawals point (NERC CEH Wallingford, 2018). The MRF policies simulated here are set at historical percentiles of the same daily flow record (**Table 6.1**).

Table 6.1. Regulation strategies to be simulated under future ensemble		
Strategy Code	**Withdrawal licence** (set at percentile of historical simulated daily water withdrawals along Arc L)	**MRF limit** (set at percentile of historical daily flow at NRFA station 38001, 1900-2000)
S.a	Q0 (1200Ml/d, current licence)	Q100 (0Ml/d)
S.b	Q0 (1200Ml/d, current licence)	Q98 (24Ml/d)
S.c	Q0 (1200Ml/d, current licence)	Q95 (45Ml/d, current MRF)
S.d	Q0 (1200Ml/d, current licence)	Q90 (68Ml/d)
S.e	Q0 (1200Ml/d, current licence)	Q85 (82Ml/d)
S.c.1	Q10 (TBC in simulation)	Q95 (45Ml/d, current MRF)
S c.2	Q20 (TBC in simulation)	Q95 (45Ml/d, current MRF)
S c.3	Q30 (TBC in simulation)	Q95 (45Ml/d, current MRF)

6.2.3 Hydro-ecological model

Multi-level linear regression modelling is used to examine the impact of future changes in flow on macroinvertebrate ecology within the Lee Valley. The use of multi-level models to analyse hydro-ecological relationships are widespread within the literature (dos Reis Oliveira et al. 2020; Klaar et al. 2014; Mellado-Díaz et al. 2019; Murdoch et al. 2020); popular as a consequence of the partially pooled analysis used and ability to build regression relationships using multi-site data. Multi-level linear modelling is well suited for this case study as macroinvertebrate observations are sparse and inconsistently recorded throughout the catchment, particularly below the reservoir withdrawal point. Here, the hydro-ecological model is built using historical antecedent flow conditions and macroinvertebrate community composition observations across several sites throughout the Lee catchment (**Figure 6.3**).

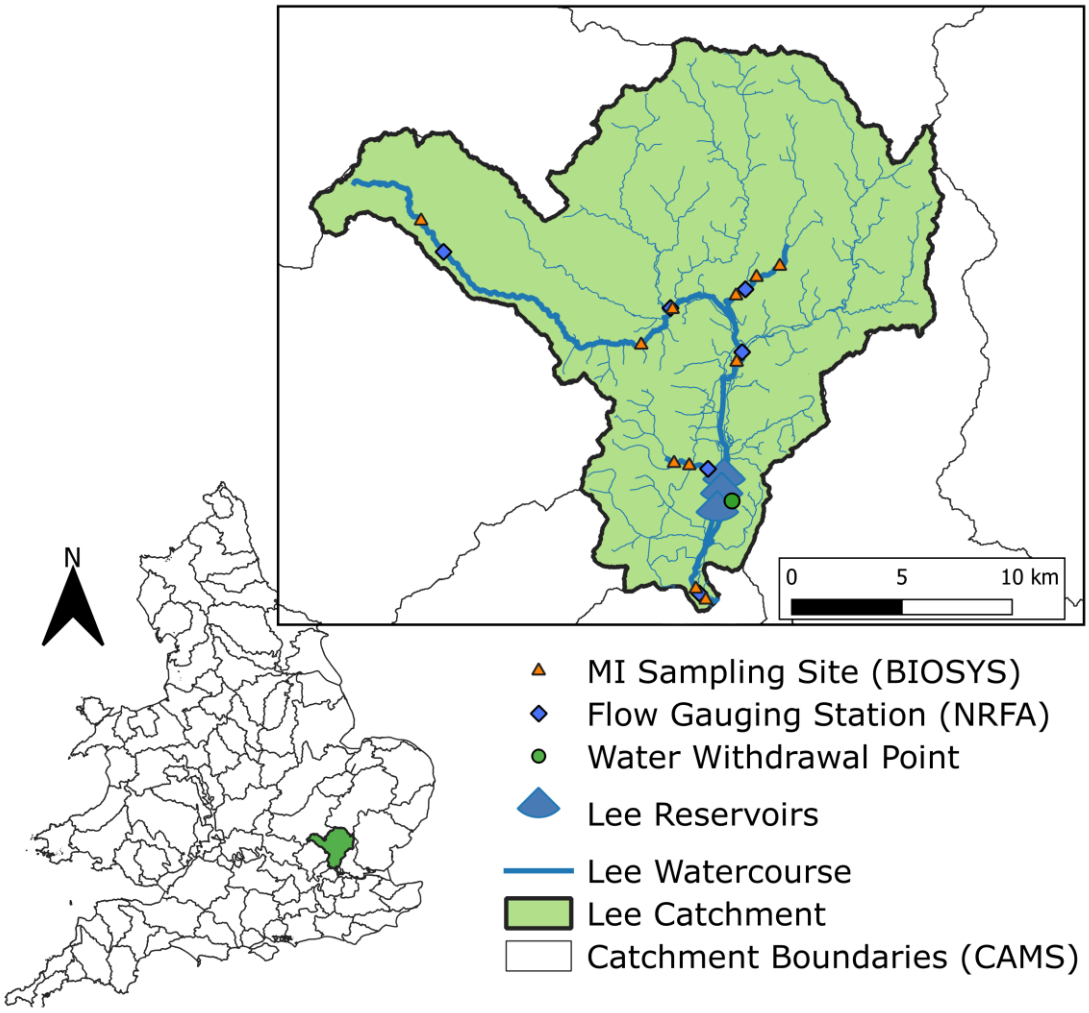


Figure 6.3. Study site. Markers indicate locations of National River Flow Archive (NRFA) gauging stations, macroinvertebrate (MI) BIOSYS sampling sites, Lee reservoirs, and Lee Reservoir withdrawals point. The Lee watercourse and Catchment Abstraction Management Strategy (CAMS; Environment Agency, 2014) boundaries are also shown.

6.2.3.1 Macroinvertebrate community composition

Macroinvertebrate community composition data were extracted from the Environment Agency BIOSYS dataset (Environment Agency, 2020). The dataset contains biannual observations collected from standardized monitoring of river sites across England and Wales, and has been used widely in hydro-ecological assessments (Clews & Ormerod,

2009; Dunbar et al. 2010; Mathers et al. 2016). Several standard biomonitoring indices of ecological and hydrological quality are derived from BIOSYS samples, including BMWP, NTAXA, ASPT, LIFE, PSI and EPT. This study uses LIFE scores as a proxy for river health, an index developed by Extence et al. (1999) to link riverine benthic macroinvertebrate community to prevailing flow regime. In general, low LIFE scores are observed during periods of reduced discharge, whilst higher LIFE scores indicate faster flow velocities with clean substrata (Dunbar et al. 2010). For chalk and limestone streams, LIFE scores have been shown to be closely related to antecedent summer low flows. Eleven MI sampling sites were selected for the analysis (**Figure 6.3**), with 125 summer LIFE score observations (April-September) from 1990 to 2018 used in development of the hydro-ecological models. The set of sampling sites used are listed in **Appendix C3**.

6.2.3.2 Flow predictors

Each biomonitoring site is paired with the nearest flow gauging station (**Figure 6.3**; **Appendix C4**). Mean daily flows from the National River Flow Archive (NERC CEH Wallingford, 2018) are used to calculate antecedent seasonal hydrological indicators (HI) for each macroinvertebrate sample. The indicators considered are ecologically relevant and represent different facets of the flow regime, including extreme flows, low flows, high flows, and rates of change in flow (Richter et al. 1996). Consistent with other studies that evaluate macroinvertebrate response to antecedent flow conditions (Chadd et al. 2017; Dunbar et al. 2010; Extence et al. 1999), this study divides each hydrological year into two periods: summer flows (April-September) and winter flows (October-March). 30 hydrological indicators in total are considered, with 15 HIs for each seasonal period (**Appendix C5**).

All hydrological indicators considered are unitless, which is necessary when building multi-level linear regression models using data observed across multiple sampling sites (Dunbar et al. 2010). The HIs can be categorised into two groups. The first group defines HIs by flow quantiles, and are standardized relative to the long-term observations at individual gauging station locations. The standardized flow statistic, z_{im} in period i at site m, is calculated $z_{im} = \frac{(x_{im} - \mu_m)}{\sigma_m}$, where x_{im} represents the observed flow statistic in period i at site m, μ_m the long-term mean of the flow statistic at site m, and σ_m the standard deviation in the observed flow statistic record at site m. Negative z-statistics indicate below average quantile values relative to the historic record; positive z-statistics represent above average values. The second group of hydrological indicators are presented as a proportion of days within the season that satisfy set criteria, such as the proportion of days when daily flow is less than historical Q90, or the proportion of days when flow is increasing (i.e. positive reversals). These HIs do not need to be standardized because the HI is represented as a number between zero and one. Here, zero indicates no days in the season when the flow criteria are satisfied, and one indicates all days in the season satisfy the criteria.

6.2.3.3 Statistical methodology

This study follows a modified version of the statistical methodology presented by Dunbar et al. (2010), who use sampling site location as a grouping variable in the multi-level linear regression model. The multi-level model consists of fixed and random effects; fixed effects determine model intercept and slope, and explain the overall response of the model across multiple sampling sites. In the multi-level model, individual hydrological indicators from the same gauging station represent the 'within site' level of the model and are expressed as fixed effects. In line with Dunbar et al. (2010), random effects explain variation around

the overall LIFE score response. The Lee hydro-ecological model developed here is classified as multi-level because random effects exist at two levels: among sampling sites and within sampling sites.

Multi-level hydro-ecological models using different combinations of HI are investigated following the flowchart presented in

Figure *6.4*. In developing the model, we test the hypothesis that antecedent flow in the preceding two seasons before a macroinvertebrate sample influences macroinvertebrate health. This is consistent with other studies that have tested the effect of seasonal antecedent flow conditions, including Chadd et al. (2017), Worrall et al. (2014), Dunbar et al. (2010), and Dunbar, Warren, et al. (2010). The R packages *Glmulti* (Calcagno, 2013) and *lme4* (Bates et al. 2015) are used to fit multi-level models with HIs from the winter and summer season preceding a summer macroinvertebrate sample. *Glmulti* exhaustively screens candidate models, examining all possible combinations of HIs for a given number of model terms. Models are first fit with one term, increasing in complexity with each screening. The models from each screening are ranked according to Akaike Information Criterion (AIC) and the top 100 from each screening are used in the next stage of model development. Candidate model screening is terminated when all estimated coefficients for the multi-level models of a given screening are non-significant (*p-value* > 0.05). Next, the top 100 models from each screening stage are pooled and ranked again using AIC. Starting from the best model, the models are evaluated sequentially. A model is rejected if it contains (i) non-significant fixed effect parameter coefficient estimates, or (ii) more than one HI that describes similar facets of the flow regime in the same season (see **Appendix C5)**. The first model to satisfy the selection criteria is used for macroinvertebrate index simulation.

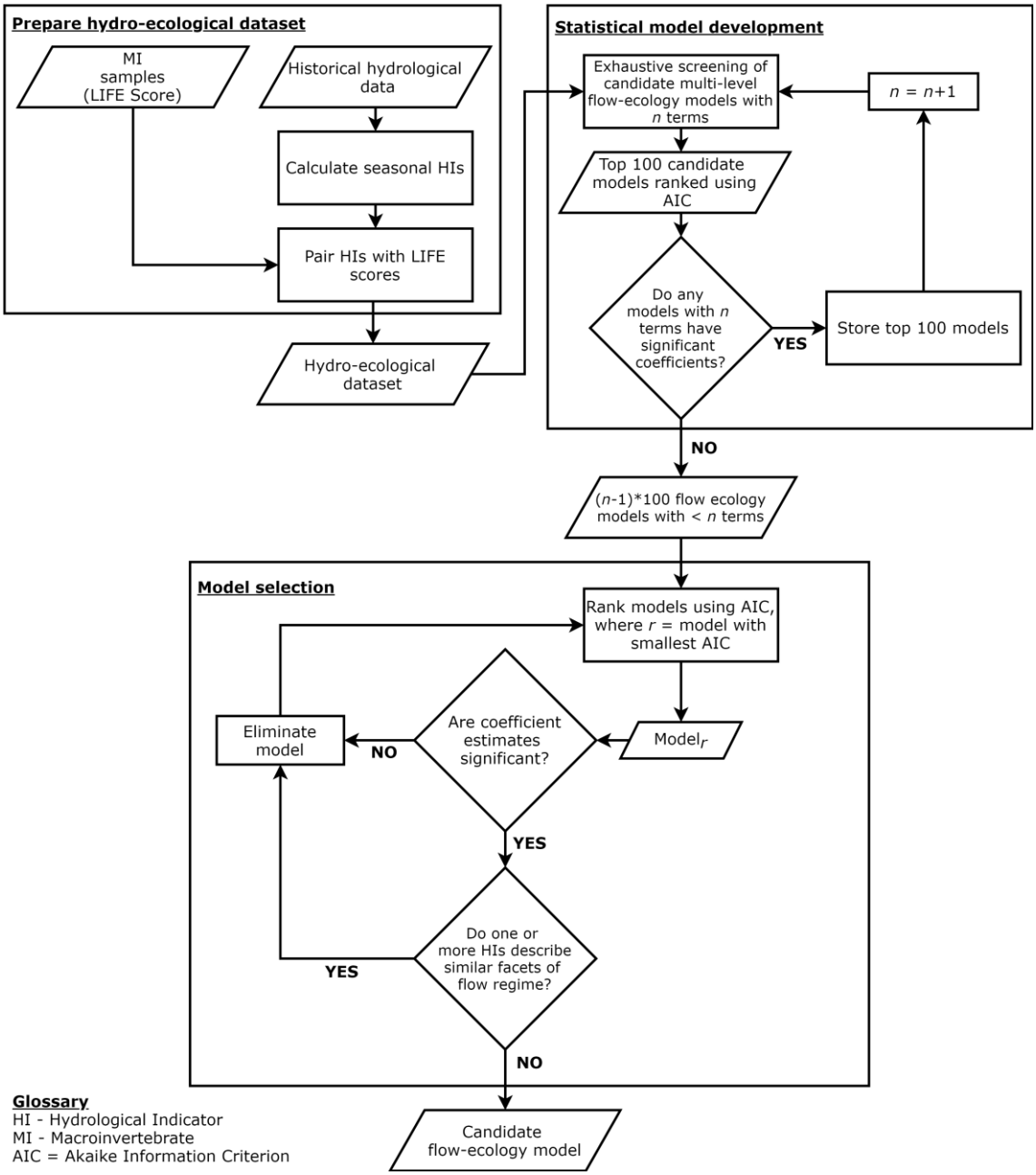


Figure 6.4. Process of selecting candidate multi-level linear hydro-ecological model.

6.2.4 Macroinvertebrate index simulation

Upon selecting suitable HIs for the candidate hydro-ecological model, the model is used to simulate LIFE scores along Arc M in the Historic, Baseline, Near Future and Far Future periods. Here, Arc M is treated as a new sampling site. Because the hydro-ecological model is built with a partially pooled analysis using data from multiple sites throughout

the Lee catchment, the regression relationship derived for Arc M is skewed towards the overall relationship for all sampling sites used in the study. This 'borrowed strength' is advantageous in predicting macroinvertebrate response for sites with scarce data (Dunbar et al. 2010; Gelman & Hill, 2007).

Hydrological indicators for Arc M are calculated using the same procedure described in **Section 6.2.3.2**. The system model is first run under a 'do nothing' strategy (Strategy S.c) using the Historic scenario to establish historical hydrological indicators for Arc M. For hydrological indicators defined by flow quantiles, the mean μ_a and standard deviation σ_a of the explanatory flow quantile is derived from the Historic simulation and used to standardize the equivalent flow statistic in future simulations. For example, in simulations under future conditions the flow quantile x_{ia}, at site a (Arc M), is transformed into the standardized hydrological indicator, z_{ia}, in period i, according to $z_{ia} = \frac{(x_{ia}-\mu_a)}{\sigma_a}$. For HIs that represent the proportion of days in a season that satisfy set criteria, the criteria are again calculated using seasonal flow statistics along Arc M from the Historic simulation. For example, the proportion of days in a summer season when flow is less than historic summer Q90 is calculated using the long-term summer Q90 from the Historic simulation. The calculation can be written: $p_{ia} = \frac{\sum_{t=1}^{n} \mathbf{1}_{f_{ta}<x_{ha}^{v}}(f_t)}{n}$, where p_{ia} is the proportion of days at site a in period i with n days, when flow f_t is less than the flow statistic x_{ha}^{v}, where x is derived from the Historic simulation h at site a in season v (where season v can be winter or summer). The workflow is designed to ensure that all future simulated HIs are scaled relative to historic conditions observed under simulations of the current water withdrawal strategy and water supply infrastructure.

To account for uncertainty when predicting LIFE score, we estimate the distribution of residuals in the historically observed data using a non-parametric kernel

distribution estimator. For the candidate multi-level linear regression model, we calculate the non-parametric estimation of the probability density function (pdf) of the model residuals. A randomised predictor of LIFE score is then generated for each simulated observation by sampling from the estimated distribution. The sample is then added to the LIFE score calculated from the multi-level linear regression model using the same observation period. The final predicted LIFE scores represent the statistical relationship between antecedent flow conditions and macroinvertebrate community response, and reflect the residual uncertainty in macroinvertebrate community response. The workflow for simulating future LIFE scores can be summarised:

(i) Estimate coefficients, $\hat{\beta}_0$ and $\hat{\beta}_1$ to $\hat{\beta}_w$ for candidate multi-level linear regression model:

$$LIFE_{im} = \beta_0 + \beta_1 D_{im}^1 + \beta_2 D_{im}^2 + \ldots + \beta_k D_{im}^k + b_{0m} + \varepsilon_{im}$$

where $LIFE_{im}$ represents the LIFE score observation in period i at level (site) m, β_0 denotes the intercept term, β_1 to β_k are the hydrological indicator coefficients for D_{im}^1 to D_{im}^k, which signify the hydrological indicator in period i for level m, b_{0m} represents the random effect for level m, and ε_{im} the error term for observation in period i at level m.

(ii) Calculate the estimated residual, $\hat{\varepsilon}_{im}$, for each LIFE observation:

$$\hat{\varepsilon}_{im} = LIFE_{im} - \hat{\beta}_0 - \hat{\beta}_1 D_{im}^1 - \hat{\beta}_2 D_{im}^2 - \ldots - \hat{\beta}_k D_{im}^k - \hat{b}_{0m}$$

(iii) Fit non-parametric distribution Ω to estimated residuals $\{\hat{\varepsilon}_{im}\}_{i=1,\ldots,R,m=1,\ldots,J}$

(iv) Simulate LIFE score at site a in period i:

$$LIFE_{ia} = \hat{\beta}_0 + \hat{\beta}_1 D_{ia}^1 + \hat{\beta}_2 D_{ia}^2 + \ldots + \hat{\beta}_k D_{ia}^k + b_{0a} + \tilde{\varepsilon}_{ta}$$

where $\tilde{\varepsilon}_{ta} \sim \Omega$.

6.3 Results

6.3.1 Hydro-ecological model fit and forecast skill

Multi-level hydro-ecological models were built using paired historical flow and macroinvertebrate observations. The final set of candidate hydro-ecological models are listed in **Appendix C6** and are ranked according to AIC. Ten models in the top 20 consisted of three HIs, each reflecting facets of the flow regime in the summer and winter season prior to MI sampling. The most common summer HIs selected for the multi-level model included standardized Q90 ($\mathrm{Q90z}_S$) or Q80 ($\mathrm{Q80z}_S$), and/or measures of the proportion of days in which flow exceeds extreme historical flow percentiles ($MT\mathrm{Q10}_S$ or $LT\mathrm{Q90}_S$). The most frequently selected winter HIs describe average flow conditions ($MT\mathrm{Q50}_W$ or $LT\mathrm{Q50}_W$) or mild flow events ($MT\mathrm{Q30}_W$ or $LT\mathrm{Q70}_W$). The pattern of HI selection in the final stage of model development indicates that LIFE scores in the Lee Valley are susceptible to changes in extreme flow conditions in summer, and flow stability relative to the mean conditions in winter. Interestingly, HIs representing rates of change in flow (positive/ negative reversals) did not feature in the final set of hydro-ecological models. This suggests that HIs representing the magnitude and extent of the flow regime are more relevant for evaluations of river health in the Lee Valley (although this is not necessarily true for all catchments).

The model selected for future simulations consists of hydrological indicators corresponding to: (i) the proportion of days in the summer preceding a LIFE score observation with flow greater than the historical Q10 ($MT\mathrm{Q10}_S$), (ii) the standardized summer Q90 ($\mathrm{Q90z}_S$) in the summer preceding a LIFE score observation, and (iii) the proportion of days in the winter immediately preceding a LIFE score observation with flow less than the historical Q50 ($LT\mathrm{Q50}_W$). **Table 6.2** lists the parameters of the multi-level hydro-ecological model, including the parameter coefficients and corresponding *p*-

values. **Figure 6.5a** highlights the timing of seasonal HI observations for the candidate model. The parameter estimate for $Q90z_S$ suggests that above average summer low flows will positively influence LIFE scores, whilst below average low flows will be harmful for river health. In contrast, a high proportion of days in summer when flow exceeds historic Q10 will negatively influence LIFE scores. Together, the parameter estimates for $MTQ10_S$ and $Q90z_S$ suggest that river health in the Lee may be vulnerable to extreme low and high flow events in the summer preceding a MI sample. The negative parameter estimate for $LTQ50_W$ suggests that average winter conditions have greater control over LIFE scores than extreme winter flows, with an increase in the proportion of days below the historical winter Q50 resulting in lower LIFE scores. **Figure 6.5d**, **e** and **f** illustrate the interaction of $MTQ10_S$, $Q90z_S$ and $LTQ50_W$ with summer river health, showing the mean site and individual site relationships between HIs and LIFE score.

To account for variability in the fitted LIFE response around the model regression line, we use the kernel density estimator to estimate the pdf of the model residuals. **Figure 6.5b** plots the model residuals versus the fitted LIFE values, which are used to estimate the pdf presented in **Figure 6.5c**. When simulating future LIFE scores, a randomised predictor of LIFE score is sampled from this pdf and added to the predicted LIFE score from the multi-level model.

Table 6.2. Parameters of candidate hydro-ecological model.			
	Parameter	**SE**	**P-value***
Fixed effects			
Intercept	6.604	0.196	<0.001
$MTQ10_S$	-0.967	0.367	0.009
$Q90z_S$	0.137	0.044	0.002
$LTQ50_W$	-0.263	0.112	0.021
Random effects^{+}			
Intercept	0.570		
Residual	0.294		
***Based on T-tests, $^{+}$Expressed in LIFE score units			

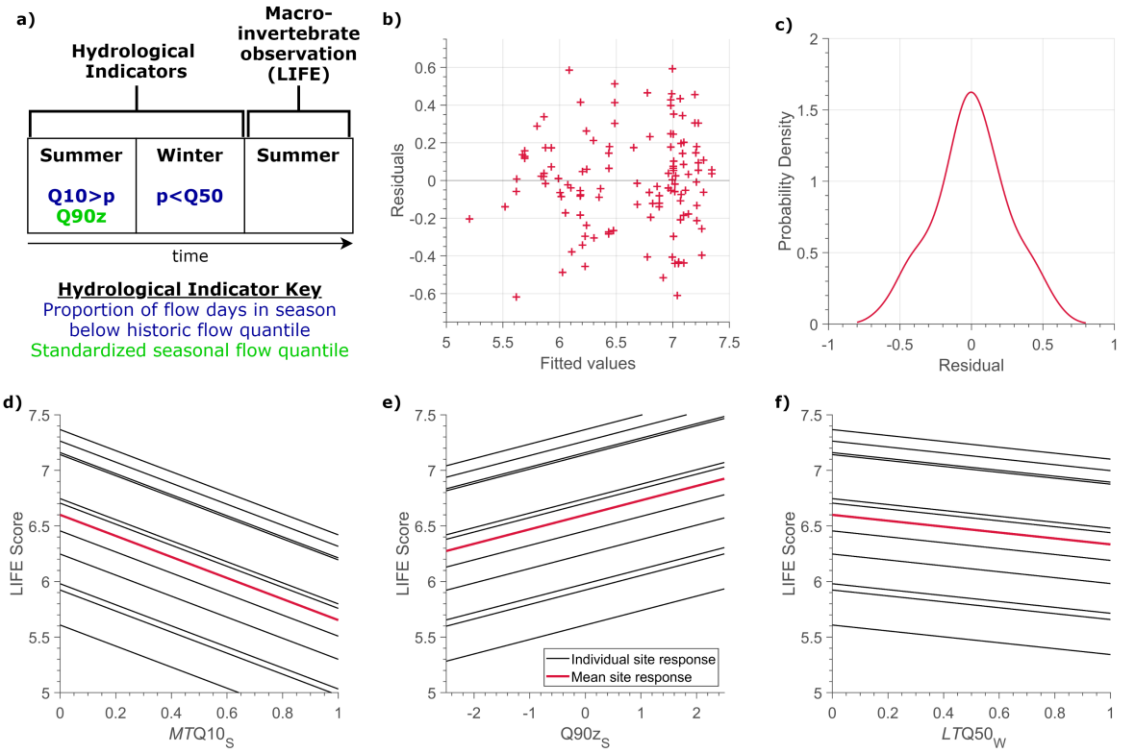


Figure 6.5. Features of the candidate hydro-ecological model. **a** presents timeline of model terms and MI sampling. **b** plots the model residuals versus fitted LIFE scores. **c** shows the probability density curve of model residuals derived from kernel density estimator. **d** illustrates Lee hydro-ecological model using antecedent $MTQ10_S$ as a predictor, with

$Q90z_S$ and $LTQ50_W$ held constant. **e** illustrates Lee hydro-ecological model using antecedent $Q90z_S$ as a predictor, with $MTQ10_S$ and $LTQ50_W$ held constant. **f** illustrates Lee hydro-ecological model using antecedent $LTQ50_W$ as a predictor, with $MTQ10_S$ and $Q90z_S$ held constant. In figures **d** to **f** the red line indicates overall relationship at the mean sampling site; black lines indicate individual site relationships between HI and LIFE score.

6.3.2 Macroinvertebrate simulation

This section presents simulated summer LIFE scores for the stretch of river below the Lee reservoir withdrawal point (Arc M) for the different regulation strategies (**Table 6.1**) when simulated against the Historic scenario (1962-2015), and Baseline (1975-2004), Near Future (2020-2049), and Far Future (2070-2099) ensembles. The results explore the difference between simulated LIFE scores under the strategies, identifying policies that help to maintain river health in the Lee Valley under increasing climate and demand side pressures. The results primarily focus on strategy performance in the Near and Far Future simulations, as these simulations use RCP-driven flow scenarios. However, simulation results from the Baseline ensemble are also presented for reference.

Figure 6.6a presents the kernel density estimated pdf of simulated summer LIFE scores under Strategy S.c. This strategy represents the current system state without changes to regulatory policies. The Historic pdf is represented by the orange line, Baseline by green, Near Future by blue and Far Future by red. Simulations of the W@H ensembles result in a shift in mean LIFE score distribution towards lower LIFE scores, with lower mean and minimum simulated LIFE scores relative to the Historic simulation (**Appendix C7**). This is attributed to the increased demand pressures in the three ensembles, and decreased water availability in the Near and Far Future ensembles. The range of simulated LIFE scores increases in both Near and Far Future simulations, with higher maximum

simulated LIFE scores estimated for the future ensembles compared to the maximum score simulated under Historic conditions. **Figure 6.6b**, **c** and **d** illustrate the shift in simulated LIFE scores in the three future ensembles away from the scores simulated under Historic conditions. The plot presents ecdfs of the range and mean simulated LIFE scores, with the shaded areas representing the range of simulated LIFE scores observed between individual scenarios in the ensembles. **Figure 6.6b** shows that LIFE scores simulated under Historic conditions fall within the range of scores simulated under the Baseline ensemble. **Figure 6.6c** and **d** indicate that the range of simulated LIFE scores will narrow and shift towards lower scores throughout the 21st Century. The overall shape of the cdfs and pdfs imply that without adaptation, mean LIFE scores will decrease over time, with higher scores becoming increasingly unlikely by the 2070s.

The change in distribution of simulated LIFE scores over time is attributed to lower simulated $Q90z_S$ and higher simulated $LTQ50_W$ values along Arc M in the Near and Far Future ensembles, relative to the Historic scenario. Ecdf plots of the hydrological indicators in the Near and Far Future periods are presented in **Appendix C8**. Looking at $Q90z_S$, a distinct decrease is observed over time between the Historic, Near, and Far Future periods, caused by an increase in the number of days in the summer season when flow along Arc M equals the minimum flow requirement. In the Far Future ensemble, summer flows are dominated by the MRF, resulting in over 80% of days in the simulation when flows equal Strategy S.c's MRF of 45Ml/d. The Near and Far Future ensembles also experience an increase in the proportion of days in winter with flow less than the historic Q50 ($LTQ50_W$), suggesting that medium to high winter flow volumes in the Lee river will decrease throughout the 21st Century.

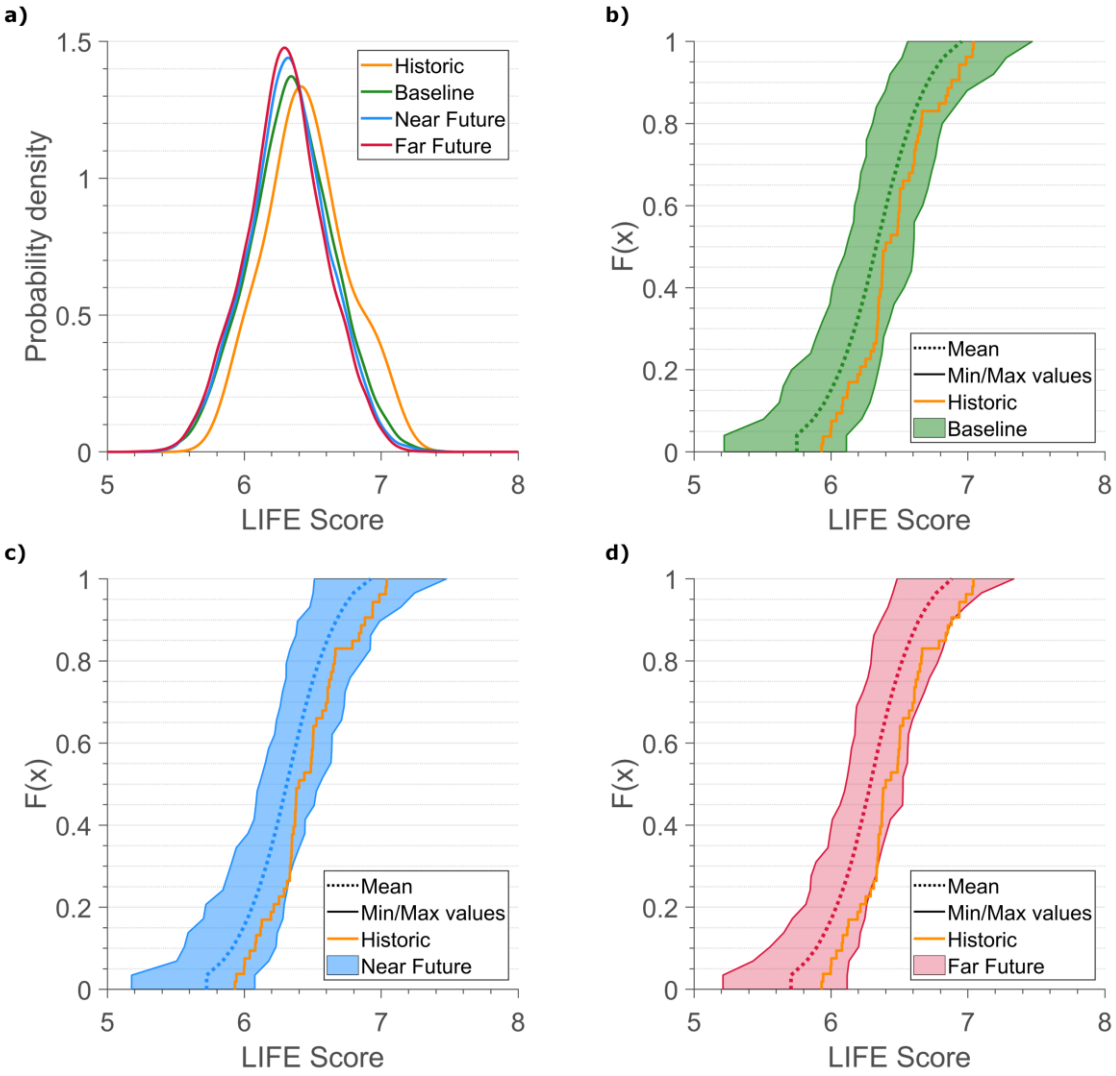


Figure 6.6. Distribution of simulated LIFE scores under Strategy S.c. **a** plots the Kernel density estimated pdf of simulated LIFE scores from simulations of Strategy S.c under the Historic scenario, and Baseline, Near Future and Far Future ensembles. **b**, **c** and **d** plot the empirical cumulative distribution of individual scenarios of simulated LIFE scores from simulations of Strategy S.c under the Baseline, Near Future and Far Future conditions, respectively. The solid lines show the range (minimum/ maximum) of simulated LIFE scores in the W@H ensemble; dashed lines show the mean simulated LIFE scores in the W@H ensembles; orange line represents the empirical cdf for the Historic simulated LIFE scores.

Figure 6.7 illustrates the trade-off between river health and water supply under increased demand and supply side pressures in the Far Future ensemble. The surface plot shows the average simulated LIFE score achieved for a given volume of total seasonal water withdrawals (abs, Ml) under Strategy S.c. Surface colour represents the simulated LIFE score calculated for the summer following one year (summer + winter) of withdrawals, with blue shades indicating high LIFE scores and red representing low scores. Where multiple LIFE scores are achieved under the same combination of summer and winter abstractions, the average LIFE score is plotted. The highest LIFE scores (>6.5) are principally observed following years with low seasonal water withdrawals, with the exception of the rightmost part of the graph. This anomaly arises from LIFE scores simulated following years with higher than average winter flows (i.e. a low $LTQ50_W$ value) and consistently high water withdrawals. The lowest LIFE scores (<6.5) are simulated following years with high summer total abstractions. This pattern emerges as a consequence of increased pressures in the future simulations. Under high water stress, water companies increase the size of daily water withdrawals, abstracting as much water from the river as the withdrawal policy and MRF regulation allows. Given that the Near and Far Future ensembles contain scenarios with increased demand and supply side pressures, flow along Arc M in future simulations will be at the lowest permissible level for longer durations relative to the Historic simulation. This impacts the HI values used to simulate LIFE scores in the hydro-ecological model, thus producing lower simulated LIFE scores.

A decrease in years with low total winter abstractions also emerges between the Historic, Near, and Far Future ensembles (not plotted), attributed to a greater requirement for winter withdrawals in the Far Future following dry summer conditions. Lower summer flows deplete reservoir levels, resulting in a greater need for larger and more frequent

winter abstractions. This has a noticeable impact on $LTQ50_W$, as the proportion of days when flow along Arc M is less than historical Q50 increases as winter abstractions grow in frequency and magnitude. This results in lower simulated LIFE scores relative to the earlier ensembles as winter flow conditions along Arc M become drier.

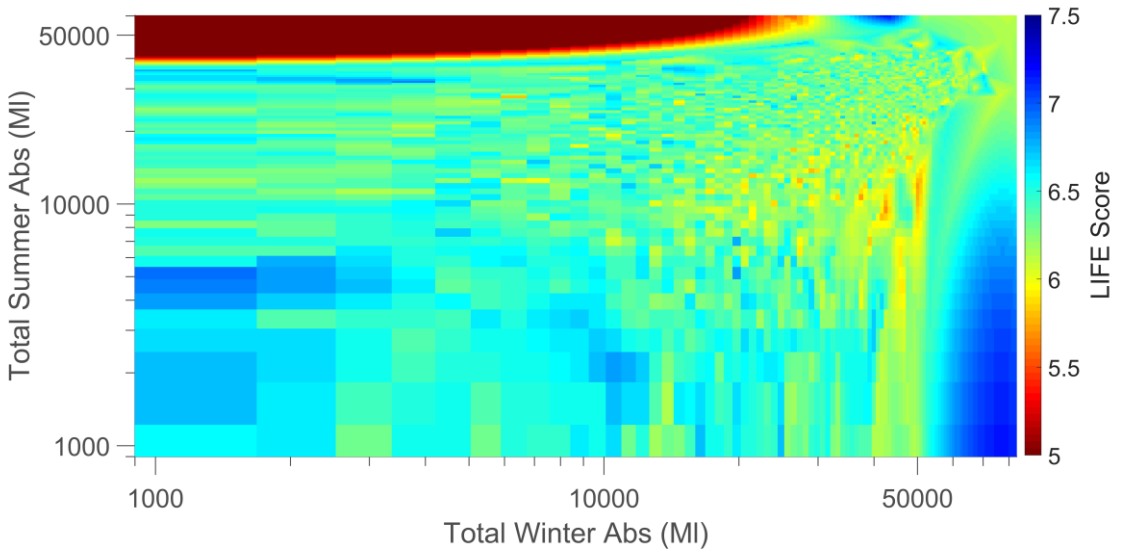


Figure 6.7. Surface plot of simulated total winter and summer withdrawals (abs, Ml) under Strategy S.c in the Far Future ensemble. Surface colour represents the simulated average LIFE score calculated for the summer following the previous year's seasonal water withdrawals.

Table 6.3 presents statistics of simulated LIFE scores achieved under the different regulation strategies when simulated against the Near and Far Future ensembles. LIFE score statistics from the simulation of Strategy S.c under the Historic scenario are also listed for comparison. Decreases to daily withdrawal licence in S.c.1, S.c.2 and S.c.3 are defined according to percentiles of the simulated daily withdrawal distribution of Strategy S.c when run under the Historic scenario (see **Appendix C9** for more information). The purpose of **Table 6.3** is to summarise the success of regulation schemes in mitigating the impact of climate change and demand side pressures on LIFE scores in the 21st Century.

Table 6.3 shows that strategies with decreased MRFs relative to the current limit result in a shift in mean simulated LIFE score towards lower scores. The lowest scores are achieved under Strategy S.a, with a mean simulated LIFE score of 6.28 in the Near Future, and 6.25 in the Far Future. This is unsurprising given lowered minimum flow requirements permit flows along Arc M to fall closer to zero. Whilst Strategy S.a would not be considered environmentally acceptable in real world policy planning, it does provide an estimate of the consequence of increased zero flow days may have on LIFE scores. The simulated impact of flow intermittence is somewhat dampened in this case study example because the hydro-ecological model is built using historic flow records with few zero flow days. However, other studies have shown that increased flow intermittence and drying states can have a controlling influence on aquatic, semi-aquatic and terrestrial invertebrate communities (England et al. 2019).

Strategies that increase the MRF along Arc M relative to S.c result in a shift in simulated LIFE score distribution towards higher scores. The strategy with the highest MRF, S.e, achieves the highest mean simulated LIFE scores of all strategies simulated, producing a mean of 6.36 across the Near Future ensemble, and 6.33 across the Far Future. By raising the MRF, S.e limits the volume of water permitted for withdrawal into the Lee Reservoirs. Whilst this change does not impact high flow events in summer ($MTQ10_S$, see **Appendix C7**), the increased MRF does ensure that flow along Arc M is higher during low flow periods. This results in more positive values of $Q90z_S$, and smaller values of $LTQ50_W$. Results from the simulation of S.e indicate that, for a given summer in the same scenario we can see up to 21.5% improvements in simulated LIFE scores compared to S.c in the Near Future ensemble, and up to 21.3% improvements in the Far Future.

Strategies with decreased daily withdrawal licences (S.c.1, S.c.2 and S.c.3) show no improvement in mean simulated LIFE score when compared to simulations of Strategy

S.c, indicating that an increased MRF is more beneficial to average simulated LIFE scores under the wider ensemble conditions. Surprisingly, mean simulated LIFE score achieved under Strategies S.c.1, S.c.2 and S.c.3 are higher for the Far Future period than the Near Future; a direct consequence of more summer seasons in the Near Future ensemble exhibiting a high proportion of days when flow along Arc M exceeds the historic simulated Q10 ($MTQ10_S$). This increase in summer high flow days is caused by two factors: (i) the Near Future DECIPHeR flow ensemble contains more summer high flow events than the Far Future (see **Appendix C2**); and, (ii) a higher volume of water is abstracted from the river during summer high flow events in the Far Future to cope with decreased overall water availability, thus reducing the value of $MTQ10_S$ along Arc M compared to equivalent measures observed under Near Future simulations (see **Appendix C8**).

Consistent with Visser et al. (2019), the results presented in **Table 6.3** reveal a decrease in variance of simulated LIFE scores between the Near and Far Future periods. This is attributed to flows along Arc M becoming more similar throughout the 21st Century; which in turn is a direct consequence of (i) more homogenous simulated inflows for the Lee Catchment under the RCP-driven ensembles, and (ii) an increased requirement for water withdrawals as demand and supply side pressures worsen. The results also reveal reduced variance of simulated LIFE scores under S.c.1, S.c.2 and S.c.3 compared to all other strategies. To compensate for the reduction in daily withdrawal limit of these strategies, larger volumes of water are taken more frequently throughout the year in future simulations. This therefore preserves flow volumes along Arc M equal to the MRF for longer durations of time. This means that differences in intra-seasonal, inter-annual, and inter-scenario flow volumes along Arc M are lessened, and thus LIFE score variation dampened. This result is reflected in the ecdfs of hydrological indicators along Arc M in

Appendix C8, which show reduced ranges of scenario ecdfs across the future ensembles under strategies with decreased withdrawal limits.

Table 6.3. LIFE score statistics achieved under regulation strategies when simulated against Historic scenario, and Near Future and Far Future ensembles.

Time period	Strategy	Mean LIFE Score	Variance in LIFE Scores
Historic (1962-2015)	S.c	6.455	0.082
Near Future (2020-2049)	S.a	6.280	0.090
	S.b	6.302	0.090
	S.c	6.322	0.088
	S.d	6.341	0.088
	S.e	6.356	0.087
	S.c.1	6.284	0.077
	S.c.2	6.286	0.077
	S.c.3	6.281	0.077
Far Future (2070-2099)	S.a	6.251	0.085
	S.b	6.275	0.084
	S.c	6.298	0.085
	S.d	6.319	0.083
	S.e	6.333	0.084
	S.c.1	6.295	0.076
	S.c.2	6.295	0.075
	S.c.3	6.295	0.076

Overall, the results indicate that of all the strategies simulated, S.e produces simulated LIFE scores in the future ensembles closest to the distribution derived from simulations using Historic conditions. This suggests that S.e will be most beneficial in maintaining

river health throughout the 21st Century, helping to mitigate against future pressures arising from increased water demand and decreased supply. By increasing the minimum required flow downstream of the reservoir withdrawal point, water companies are forced to maintain higher flow levels throughout the year thus preventing over-abstraction during low flow events.

It is important to note that none of the strategies simulated are able to reproduce the mean LIFE scores simulated in the Historic period. For this reason, a final investigation was conducted using a new strategy, S.f, which is designed to preserve and prioritise LIFE scores into the future. This strategy uses the current licence limit and MRF requirements (as with Strategy S.c), but also assigns a high positive cost to the withdrawal arc linking the River Lee and Lee Reservoirs (Arc L). This high cost directly influences the likelihood of flow through the arc, prioritising flow downstream over water withdrawals in all conditions. Under this strategy, mean total summer water withdrawals in individual scenarios in the Near and Far Future ensembles were on average 99.6% and 99.2% less, respectively, than withdrawals recorded in simulations of Strategy S.c. In winter, the equivalent measure of withdrawals decreased by 99.5% in the Near and 98.8% in the Far Future simulations. Consequently, Strategy S.f successfully maintains the mean simulated LIFE score estimated for the Historic period under S.c in the Near Future ensemble (6.479), and results in a marginal decrease in mean score in the Far Future ensemble (6.451). **Figure 6.8** presents the range and mean of simulated LIFE score ecdfs from simulations of Strategy S.f under the Near Future and Far Future ensembles, plotted alongside the ecdf of simulated LIFE scores achieved under Strategy S.c in the Historic simulation. The figure further illustrates the success of Strategy S.f in maintaining mean LIFE scores into the future, but indicates that the strategy fails to guarantee robustness to the full range of conditions present in the Near and Far Future ensembles.

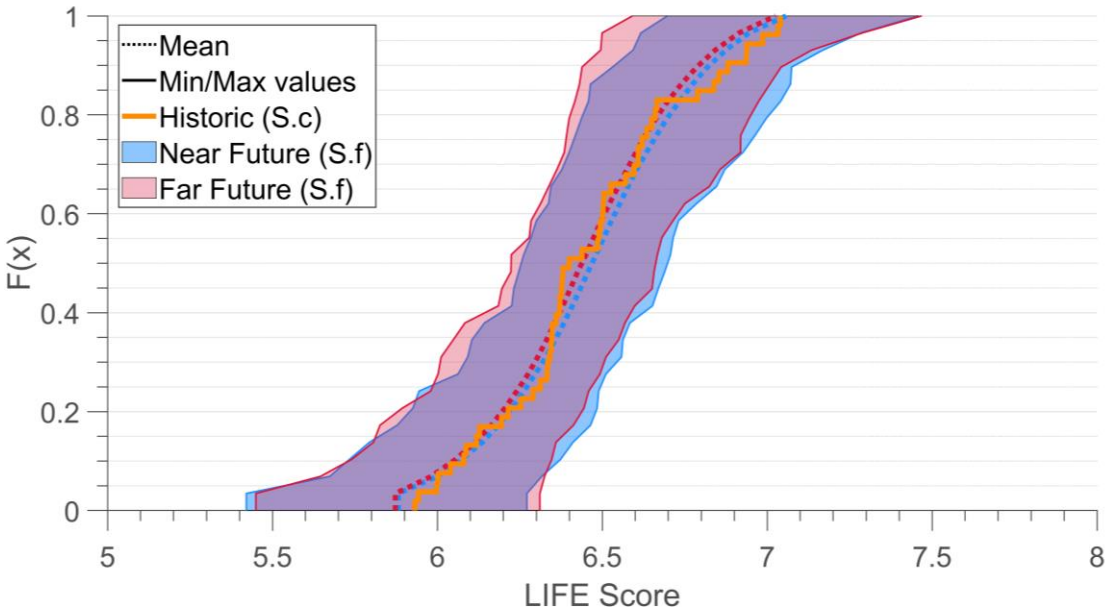


Figure 6.8. Empirical cumulative distribution function plot of simulated LIFE scores from simulations of Strategy S.f under Near Future and Far Future ensembles. The solid lines show the range (minimum/ maximum) of simulated LIFE scores in the ensemble; dashed lines show the mean simulated LIFE scores in the ensembles. The orange line represents the empirical cdf for the Historic simulated LIFE scores under Strategy S.c.

Overall, the results suggest that more stringent regulation is required to maintain river health along the lower Lee River in the mid to late 21st Century; an action that will likely come at the expense of maintaining water supply security. In the face of more stringent water withdrawals in the Lee, large infrastructure developments, such as those discussed by Borgomeo et al. (2018), will be necessary to balance the projected changes to water demand in the face of climate change and avoid over-exploitation of existing surface water supplies.

6.4 Discussion and Conclusions

Recent research has highlighted the importance of consolidating environmental science and water planning when designing riverine management portfolios (Poff, 2018). Management frameworks must recognise uncertainties inherent to long term planning, whilst also assessing trade-offs that emerge between improved water security and ecosystem health (Arthington et al. 2018). The framework and case study example presented here illustrates how this can be achieved, using a simulation driven approach that is directly linked to empirical indicators of ecological condition. The workflow can be used to test regulation strategies against climate and population driven changes in water demand and supply, offering practical guidance on how to quantify the impact of future changes on macroinvertebrate community. In doing, this provides a mechanism to effectively communicate risk to practitioners and policy makers (Acreman et al. 2014).

The empirically driven multi-level linear modelling used in this study offers a mechanism to incorporate macroinvertebrate response in water resource system simulation. The partially-pooled analysis draws on hydro-ecological relationships at other locations along the river, to (i) balance generic hydro-ecological relationships within the catchment with local relationships (Klaar et al. 2014), and (ii) allow the hydro-ecological response to be scaled to broader spatial scales (Stoffels et al. 2018). First, an exhaustive model search is used to identify flow statistics (hydrological indicators) that are most relevant to measure ecological health in the study area. This stage is important for adaptive planning problems, where indicator choice can influence policy success (Giuliani et al. 2015). The proposed search process ensures that the set of selected indicators are: (i) complete, with a combined ability to best represents the critical uncertainties that control macroinvertebrate response; and, (ii) parsimonious, thus helping to avoid increased dimensionality of the planning process by selecting unnecessary indicators (Raso et al.

2019). Upon identifying hydrological indicators to best represent the macroinvertebrate observations, the multi-level model and estimation of residual uncertainty provide the understanding necessary to regulate flow in a way most relevant to ecological response. Moreover, the BIOSYS and NRFA dataset used provides bottom-up information rarely utilised in top-down climate impact assessments (Conway et al. 2019; Westwood et al. 2017). Here, the iterative process guides practical adaptation by combining top-down emissions driven projections of 21st Century flow and population driven water demand with bottom-up site-specific observations of macroinvertebrate health and daily flow data.

The case study application further illustrates the importance of developing a clear understanding of the hydrology in the area being assessed, how it may change into the future, and the extent to which the hydrology is impacted by regulation. Achieving a comprehensive understanding in this way is difficult using only historically observed data, particularly in data sparse areas with limited monitoring of regulatory activity. By adopting simulation-based methods, we were able to decipher that, under historic conditions, water withdrawals into the Lee reservoirs are limited by water availability and minimum flow requirements, rather than the daily withdrawal licence. This understanding helped to identify regulation strategies that invoke a change in downstream flow and positively impact river health. Simulation was successfully used to explore the magnitude of regulatory action required to maintain LIFE scores into the future. Results indicate that: (i) under the current regulation policy, mean LIFE scores will decrease into the future; (ii) licence reductions prove ineffective in maintaining LIFE scores under increased demand and supply pressures; and, (iii) changes to minimum required flow constraints downstream of the withdrawal point have the greatest impact on aquatic health. In the example presented here, we expect that the impact of climate change and increased demand can be lessened only if the maximum daily withdrawal licence is greatly reduced and the MRF

below the withdrawal point is increased. In rivers where withdrawal volumes are more frequently limited by regulatory licences, we expect that smaller decreases in licence limits will protect LIFE scores downstream from future impacts of climate change and growing demand.

Whilst scenario-driven assessments are common in the water planning and management literature, they are rarely explored in environmental flow literature. The results presented here further emphasise the necessity to assess river management portfolios against uncertain future scenarios. Assessments of regulatory policies using only historic conditions fail to consider hydro-ecological response under events not present in the observed record. This is especially evident here, as the Historic scenario contains fewer low flow events of the same severity and intensity as the future ensembles. As Visser et al. (2019) found, emissions driven changes in hydrology may result in increased probability of extreme hydro-ecological response, thereby increasing risk of damage to macroinvertebrate community and ecosystem functionality. Furthermore, a scenario-based approach can be used by practitioners to quantify the likelihood of macroinvertebrate change into the future, thus aiding decision makers in their evaluation of strategy performance and impact. To ensure that a regulation strategy is well suited to the decision maker's tolerability to risk, the simulated hydrological indicator values, multi-level linear model and fitted residual distribution can be used to identify exceedance probabilities of achieving specific LIFE scores in the future ensembles. Using the visualisation tools presented in this paper, the decision maker can identify the likelihood of maintaining historically observed conditions and decide if the strategy sufficiently protects simulated LIFE scores against future environmental conditions.

There is considerable scope to improve the framework presented here. For example, future work could investigate regulatory arrangements that target features of the

hydrological regime identified as important to maintaining LIFE scores. Upon selecting a regulation strategy, the water planner can use careful monitoring to ensure that key hydrological indicators are maintained at the level required to achieve acceptable LIFE scores. The framework could also be used to enhance existing approaches of water supply investment and policy planning, which commonly trade-off metrics of water supply (e.g. risk, robustness) against the capital and operating cost of adaptation (Borgomeo et al. 2016; Herman & Giuliani, 2018; Matrosov et al. 2015; Mortazavi-Naeini et al. 2012). Macroinvertebrate response, as simulated here, could be used as a proxy for river health and incorporated into existing multi-objective planning approaches as an objective to maximize. The subsequent decision-making framework could be used to identify water supply and demand management options that are robust to future uncertainties, whilst being cost effective, risk-averse and environmentally beneficial. This would provide a much-needed move towards holistic water system planning that considers the complexity of interactions between hydrology, demand, water system management and aquatic health.

6.5 Appendix C: Supplementary materials to Chapter 6

6.5.1 Appendix C1

Supplementary Table 6.1. Performance of DECIPHeR model's ability to capture range of hydrological historical behaviour [from Coxon et al. (2019)].

Evaluation period	**1975-1977**		**1990-1992**		**2002-2004**	
NSE metric	logNSE	NSE	logNSE	NSE	logNSE	NSE
Thames at Teddington (NRFA 39001)	0.86	0.86	0.81	0.80	0.75	0.74
Lee at Feildes Weir (NRFA 38001)	0.65	0.71	0.48	0.58	0.34	0.37

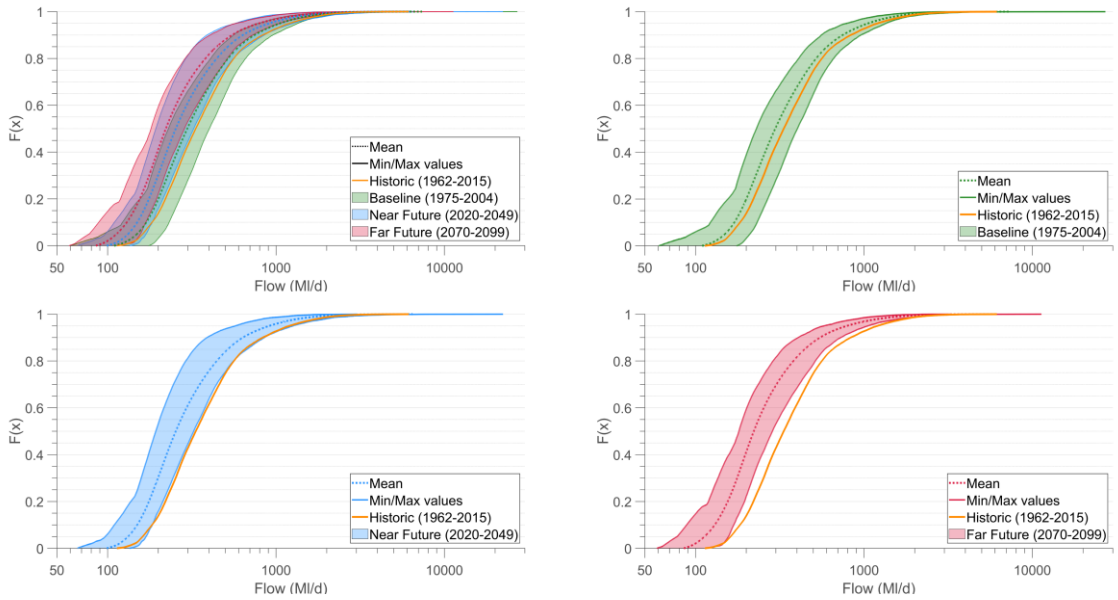
6.5.2 Appendix C2

This appendix presents empirical cdf plots of simulated flows and flow statistics from the DECIPHeR modelling framework (Coxon et al. 2019) for the Upper Lee catchment (NRFA station 38001) when run using historically observed and RCP-driven precipitation (P) and evapotranspiration (PET) time series from the CEH GEAR (Tanguy et al. 2019) and Weather@Home (W@H) platform (Guillod et al. 2017).

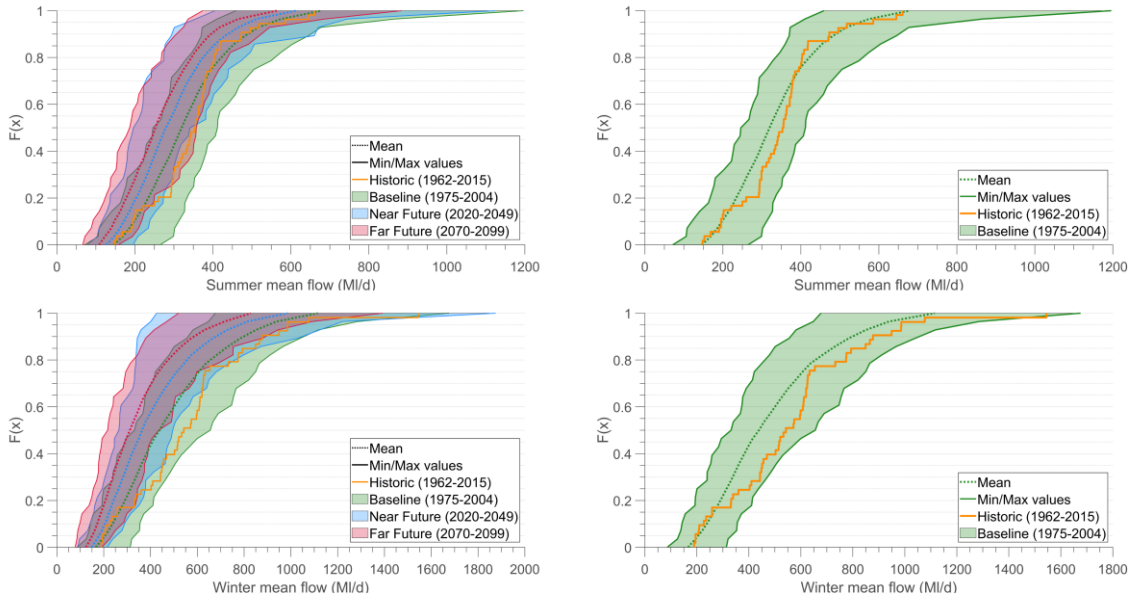
Simulated time periods:

- Historic (1962-2015) – 1 realisation, generated using historic daily observed P (Tanguy et al. 2019) and PET (Robinson et al. 2016).
- Baseline (1975-2004) – 100 realisations, generated using different initial atmospheric conditions, and historic SST and sea ice records from HadISST (Rayner et al. 2003; Titchner & Rayner, 2014).
- Near Future (2020-2049) – 100 realisations, generated using 50th percentile SST and sea ice projections (CMIP5, (Taylor et al. 2012)) under Representative Concentration Pathway (RCP) 8.5 (Meinshausen et al. 2011);
- Far Future (2070-2099) – 100 realisations, generated using 50th percentile SST and sea ice projections under RCP8.5.

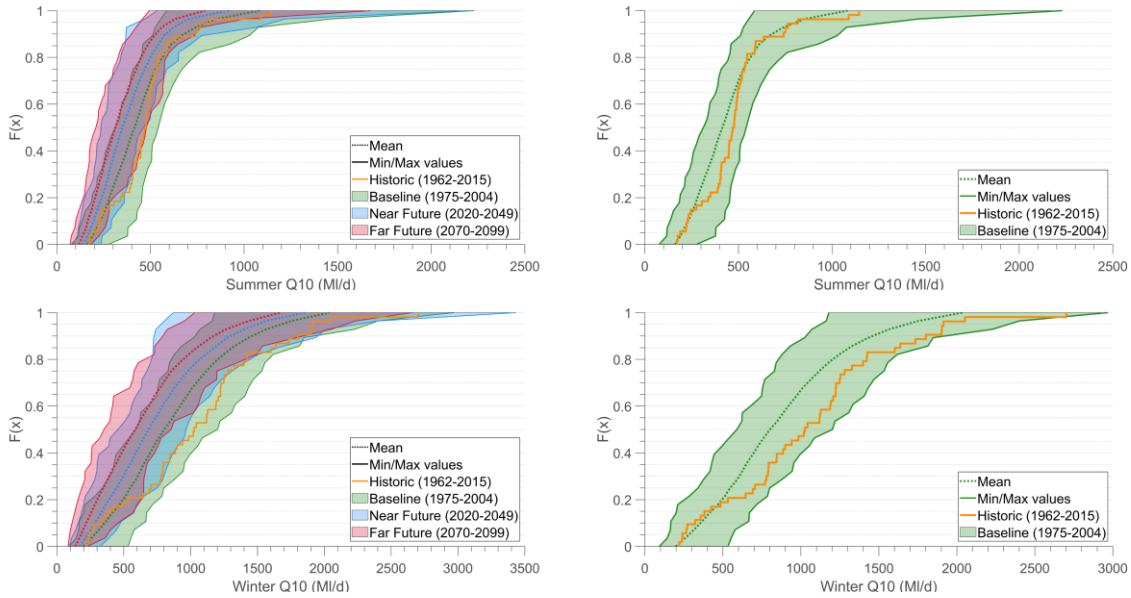
Supplementary Figure 6.1 presents empirical cdf plots of daily flows for the four simulation periods. **Supplementary Figure 6.2** to **Supplementary Figure 6.9** present empirical cdf plots of seasonal flow statistics. Summer flows represent flows from April to September. Winter flows represent flows from October to March. Qx values correspond to the flow value that is exceeded x% of the time. For example, Q10 would refer to the flow value that is exceeded 10% of the time.



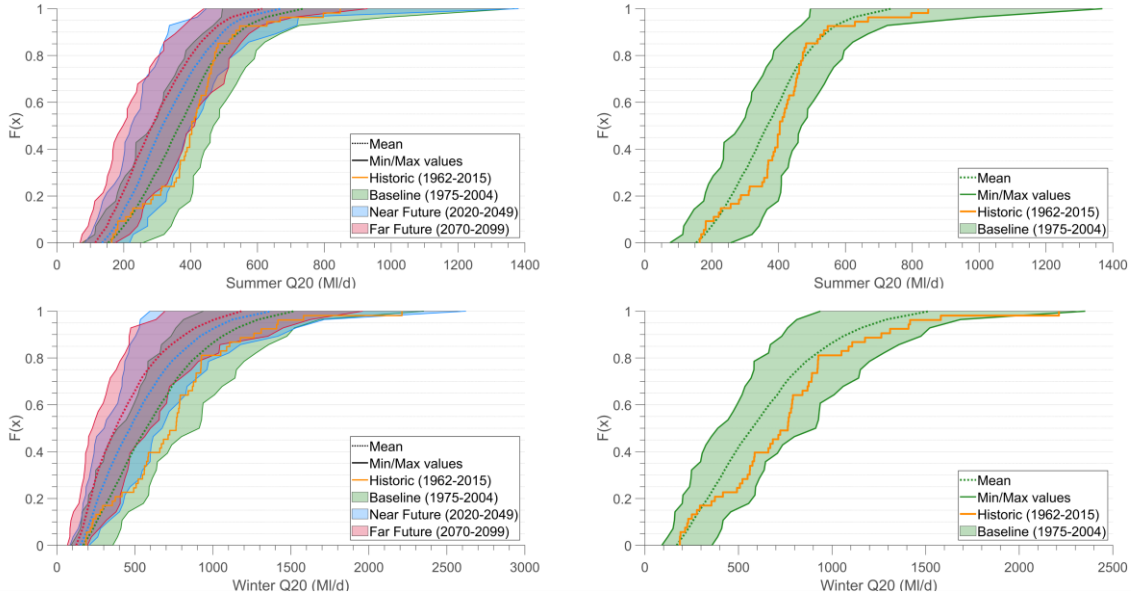
Supplementary Figure 6.1. Empirical cdfs of simulated daily flows for the Lee catchment under Historic, Baseline, Near Future and Far Future weather sequences.



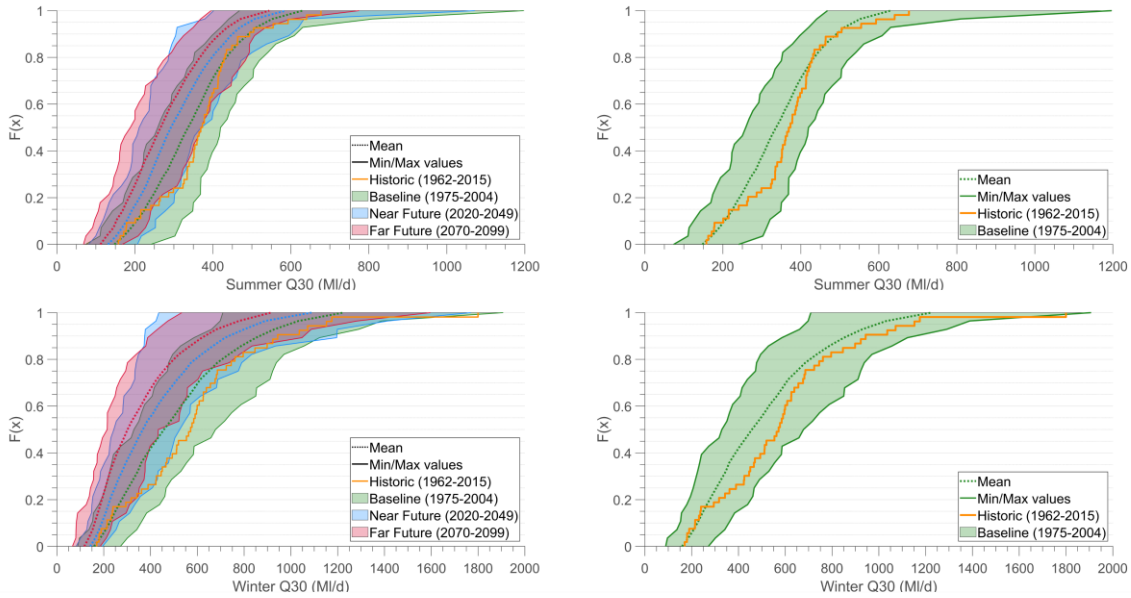
Supplementary Figure 6.2. Empirical cdfs of simulated mean summer and winter flows for the Lee catchment under Historic, Baseline, Near Future and Far Future weather sequences.



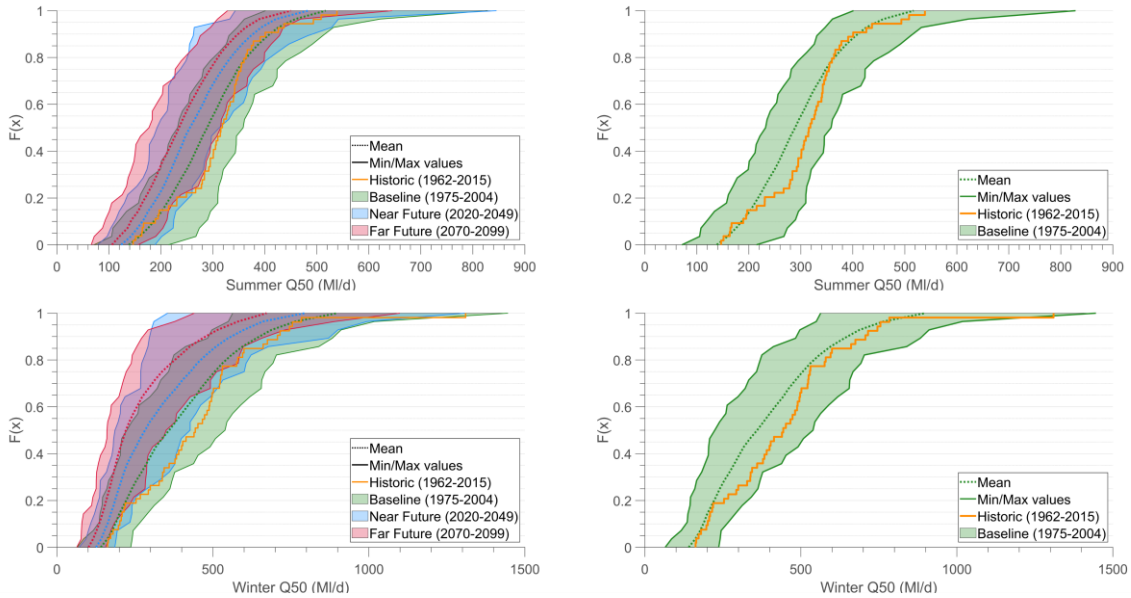
Supplementary Figure 6.3. Empirical cdfs of simulated summer and winter Q10 (10th percentile) flows for the Lee catchment under Historic, Baseline, Near Future and Far Future weather sequences.



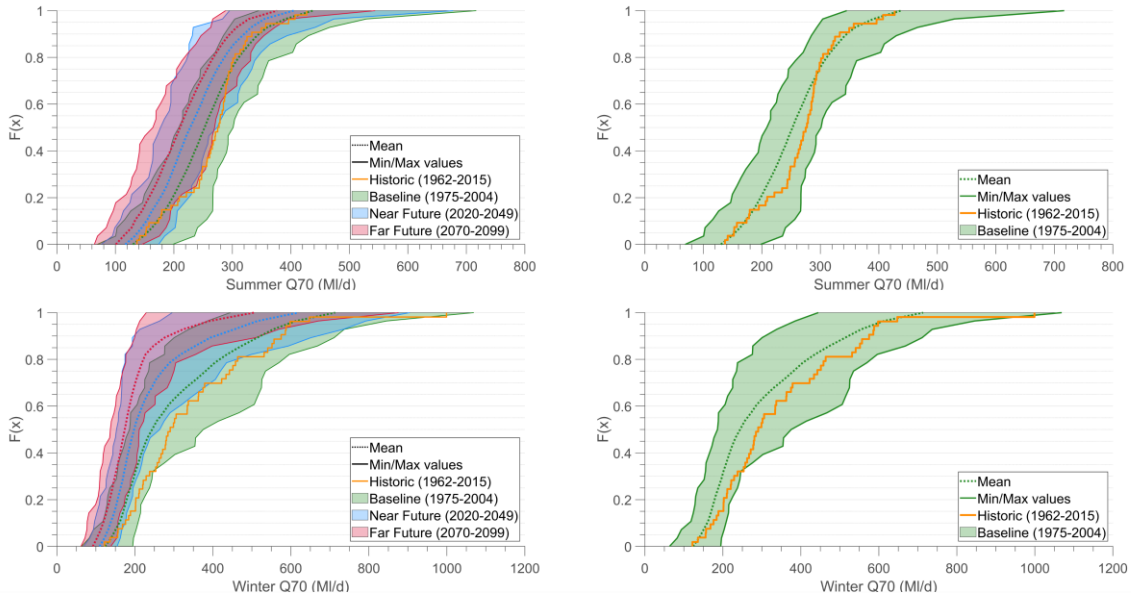
Supplementary Figure 6.4. Empirical cdfs of simulated summer and winter Q20 (20th percentile) flows for the Lee catchment under Historic, Baseline, Near Future and Far Future weather sequences.



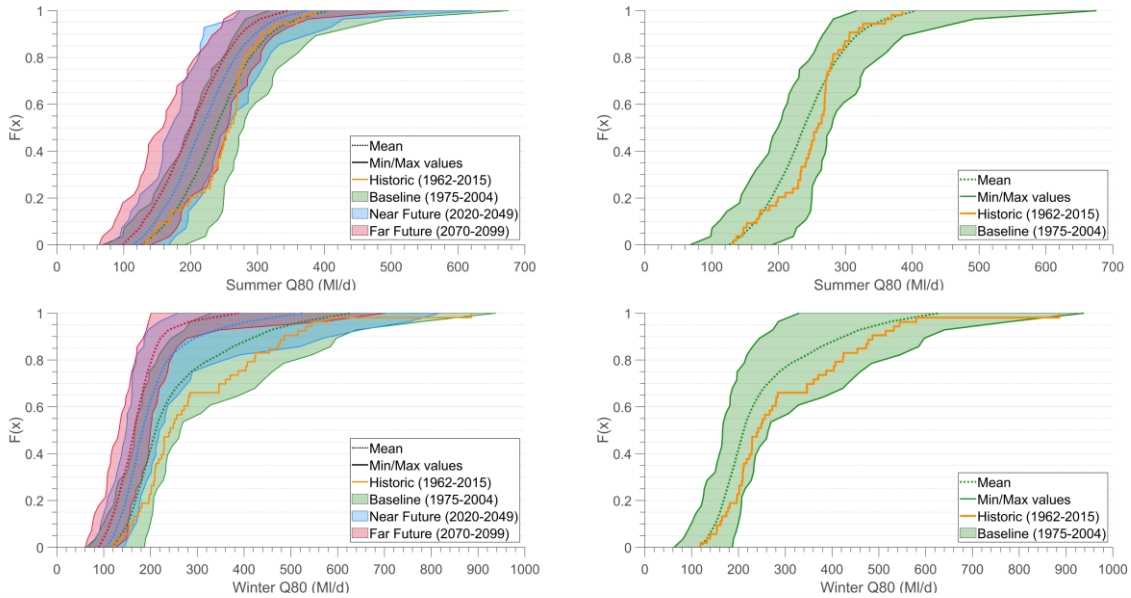
Supplementary Figure 6.5. Empirical cdfs of simulated summer and winter Q30 (30th percentile) flows for the Lee catchment under Historic, Baseline, Near Future and Far Future weather sequences.



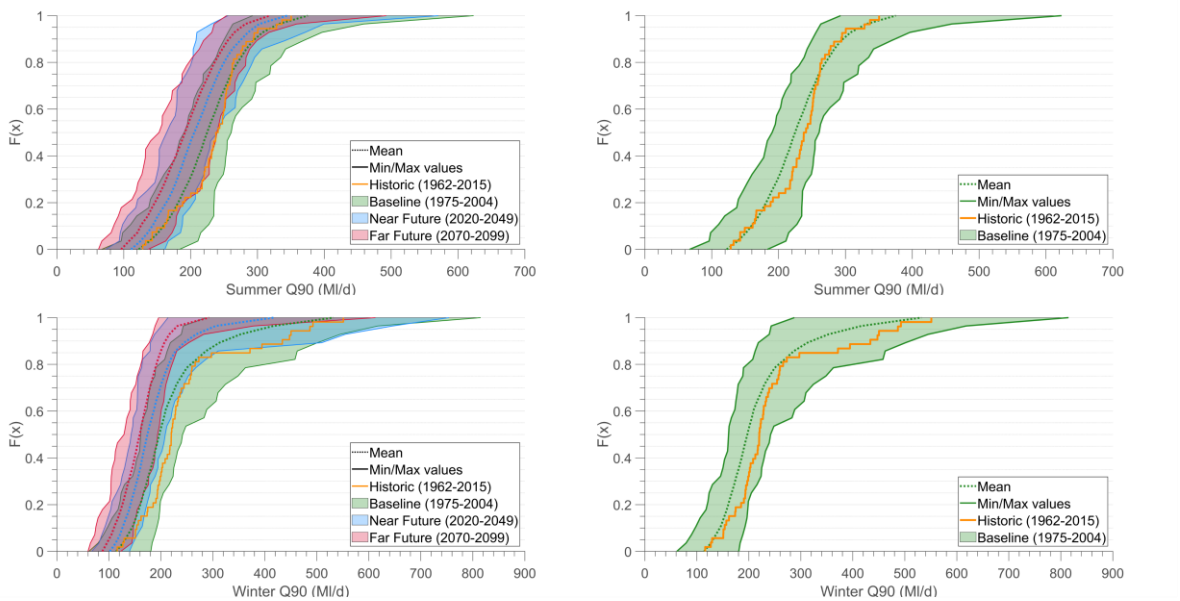
Supplementary Figure 6.6. Empirical cdfs of simulated summer and winter Q50 (50th percentile) flows for the Lee catchment under Historic, Baseline, Near Future and Far Future weather sequences.



Supplementary Figure 6.7. Empirical cdfs of simulated summer and winter Q70 (70th percentile) flows for the Lee catchment under Historic, Baseline, Near Future and Far Future weather sequences.



Supplementary Figure 6.8. Empirical cdfs of simulated summer and winter Q80 (80th percentile) flows for the Lee catchment under Historic, Baseline, Near Future and Far Future weather sequences.



Supplementary Figure 6.9. Empirical cdfs of simulated summer and winter Q90 (90th percentile) flows for the Lee catchment under Historic, Baseline, Near Future and Far Future weather sequences.

6.5.3 Appendix C3

Supplementary Table 6.2. BIOSYS sampling sites used in the study, from Environment Agency (2020).

Site number	BIOSYS ID
1	33815
2	33832
3	33836
4	33965
5	34014
6	34030
7	34156
8	34182
9	34340
10	34359
11	152883

6.5.4 Appendix C4

Supplementary Table 6.3. NRFA Gauging stations used in the study, from NERC CEH Wallingford (2018).

NRFA Station	Start date	End date	Missing data
38001	01/04/1950	01/04/2018	-
38002	01/04/1981	01/04/2018	-
38021	01/04/1972	01/04/2018	-
38030	01/04/1980	01/04/2018	-
38032	01/04/1995	01/04/2018	Data between 01/04/1997 to 31/09/1997 excluded
38033	01/04/2010	01/04/2018	-

6.5.5 Appendix C5

Supplementary Table 6.4. Hydrological indicators considered in statistical model development.

Flow group	Summer HI code	Winter HI code	Description
1	$Q98z_S$	$Q98z_W$	Standardized Q98
1	$Q95z_S$	$Q95z_W$	Standardized Q95
1	$Q90z_S$	$Q90z_W$	Standardized Q90
2	$Q80z_S$	$Q80z_W$	Standardized Q80
3	$LTQ98_S$	$LTQ98_W$	Proportion of days in season when flow is less than historical seasonal Q98
3	$LTQ95_S$	$LTQ95_W$	Proportion of days in season when flow is less than historical seasonal Q95
3	$LTQ90_S$	$LTQ90_W$	Proportion of days in season when flow is less than historical seasonal Q90
4	$LTQ80_S$	$LTQ80_W$	Proportion of days in season when flow is less than historical seasonal Q80
4	$LTQ70_S$	$LTQ70_W$	Proportion of days in season when flow is less than historical seasonal Q70
5	$LTQ50_S$	$LTQ50_W$	Proportion of days in season when flow is less than historical seasonal Q50
5	$MTQ50_S$	$MTQ50_W$	Proportion of days in season when flow is more than historical seasonal Q50
6	$MTQ30_S$	$MTQ30_W$	Proportion of days in season when flow is more than historical seasonal Q30
6	$MTQ20_S$	$MTQ20_W$	Proportion of days in season when flow is more than historical seasonal Q20
7	$MTQ10_S$	$MTQ10_W$	Proportion of days in season when flow is more than historical seasonal Q10
8	ID_S	ID_W	Proportion of days in season when flow is increasing (positive reversals)

Flow group key:
1 – Magnitude of extreme low flows
2 – Magnitude of low flows
3 – Extent of extreme low flows
4 – Extent of low flows
5 – Extent of below/ above average flows
6 – Extent of high flows
7 – Extent of extreme high flows
8 – Rate of change in flow

6.5.6 Appendix C6

Supplementary Table 6.5. Final set of candidate flow-ecology models.

Model	AIC	R^2	*P-value (95% CIs)*			
			Int	**HI 1**	**HI 2**	**HI 3**
LIFE ~ 1 + $MTQ10_S + LTQ50_W + Q90z_S + (1\|Site)$	96.672	0.766	0.000	0.009	0.021	0.002
LIFE ~ 1 + $MTQ10_S + MTQ50_W + Q90z_S + (1\|Site)$	96.762	0.766	0.000	0.009	0.022	0.002
LIFE ~ 1 + $MTQ10_S + LTQ50_W + Q80z_S + (1\|Site)$	97.242	0.764	0.000	0.008	0.029	0.003
LIFE ~ 1 + $MTQ10_S + MTQ50_W + Q80z_S + (1\|Site)$	97.333	0.764	0.000	0.008	0.030	0.003
LIFE ~ 1 + $MTQ10_S + LTQ70_W + Q90z_S + (1\|Site)$	97.957	0.764	0.000	0.022	0.044	0.006
LIFE ~ 1 + $MTQ10_S + MTQ30_W + Q90z_S + (1\|Site)$	97.968	0.763	0.000	0.010	0.044	0.001
LIFE ~ 1 + $LTQ90_S + LTQ50_W + (1\|Site)$	98.007	0.759	0.000	0.010	0.026	
LIFE ~ 1 + $MTQ30_S + LTQ70_W + Q90z_S + (1\|Site)$	98.074	0.762	0.000	0.023	0.017	0.005
LIFE ~ 1 + $LTQ90_S + MTQ50_W + (1\|Site)$	98.104	0.759	0.000	0.010	0.027	
LIFE ~ 1 + $MTQ10_S + LTQ70_W + Q80z_S + (1\|Site)$	98.188	0.762	0.000	0.017	0.050	0.007
LIFE ~ 1 + $MTQ30_S + LTQ50_W + Q90z_S + (1\|Site)$	98.295	0.761	0.000	0.024	0.020	0.004
LIFE ~ 1 + $MTQ30_S + MTQ50_W + Q90z_S + (1\|Site)$	98.394	0.761	0.000	0.024	0.021	0.004
LIFE ~ 1 + $LTQ80_S + (1\|Site)$	98.550	0.754	0.000	0.000	0.000	
LIFE ~ 1 + $LTQ90_S + LTQ70_W + (1\|Site)$	98.790	0.758	0.000	0.024	0.041	
LIFE ~ 1 + $LTQ95_S + LTQ50_W + (1\|Site)$	99.278	0.756	0.000	0.021	0.011	
LIFE ~ 1 + $LTQ95_S + MTQ50_W + (1\|Site)$	99.391	0.756	0.000	0.021	0.011	
LIFE ~ 1 + $LTQ95_S + LTQ70_W + (1\|Site)$	99.710	0.755	0.000	0.040	0.013	
LIFE ~ 1 + $MTQ10_S + Q90z_S + (1\|Site)$	100.034	0.754	0.000	0.041	0.000	
LIFE ~ 1 + $MTQ10_S + Q80z_S + (1\|Site)$	100.037	0.753	0.000	0.024	0.000	
LIFE ~ 1 + $LTQ98_S + LTQ50_W + (1\|Site)$	100.360	0.755	0.000	0.039	0.008	
LIFE ~ 1 + $LTQ98_S + MTQ50_W + (1\|Site)$	100.476	0.755	0.000	0.039	0.009	
LIFE ~ 1 + $LTQ90_S + (1\|Site)$	100.994	0.748	0.000	0.001	0.000	
LIFE ~ 1 + $LTQ70_S + (1\|Site)$	101.145	0.749	0.000	0.001	0.000	
LIFE ~ 1 + $LTQ95_S + MTQ30_W + (1\|Site)$	101.365	0.751	0.000	0.014	0.035	
LIFE ~ 1 + $LTQ90_W + (1\|Site)$	101.476	0.748	0.000	0.001	0.000	
LIFE ~ 1 + $LTQ70_W + (1\|Site)$	101.924	0.747	0.000	0.002	0.000	
LIFE ~ 1 + $LTQ80_W + (1\|Site)$	102.020	0.747	0.000	0.002	0.000	
LIFE ~ 1 + $Q90z_S + (1\|Site)$	102.237	0.745	0.000	0.002	0.000	

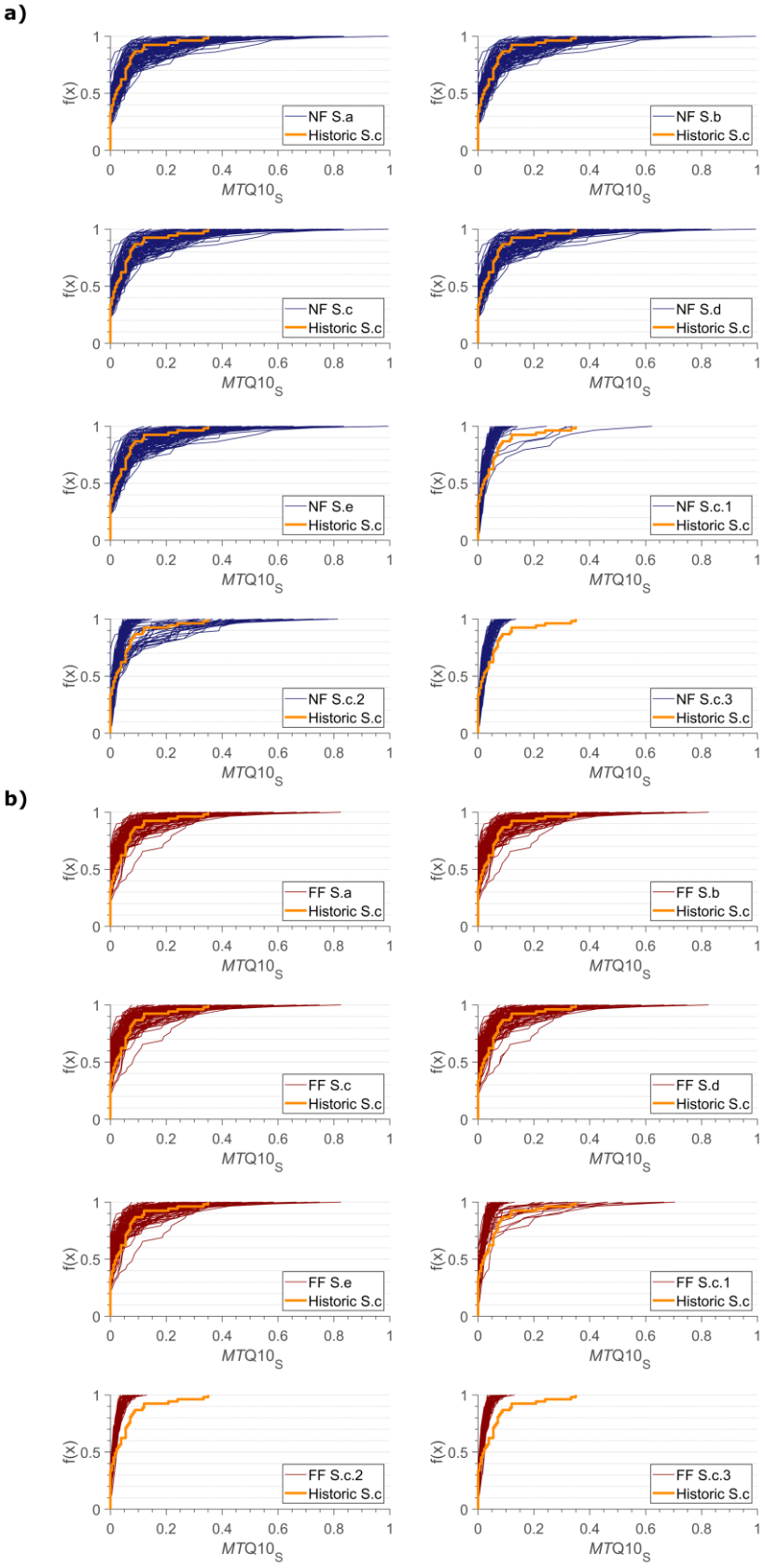
Glossary:
Int – Intercept
HI – Hydrological Indicator
AIC – Akaike Information Criterion

6.5.7 Appendix C7

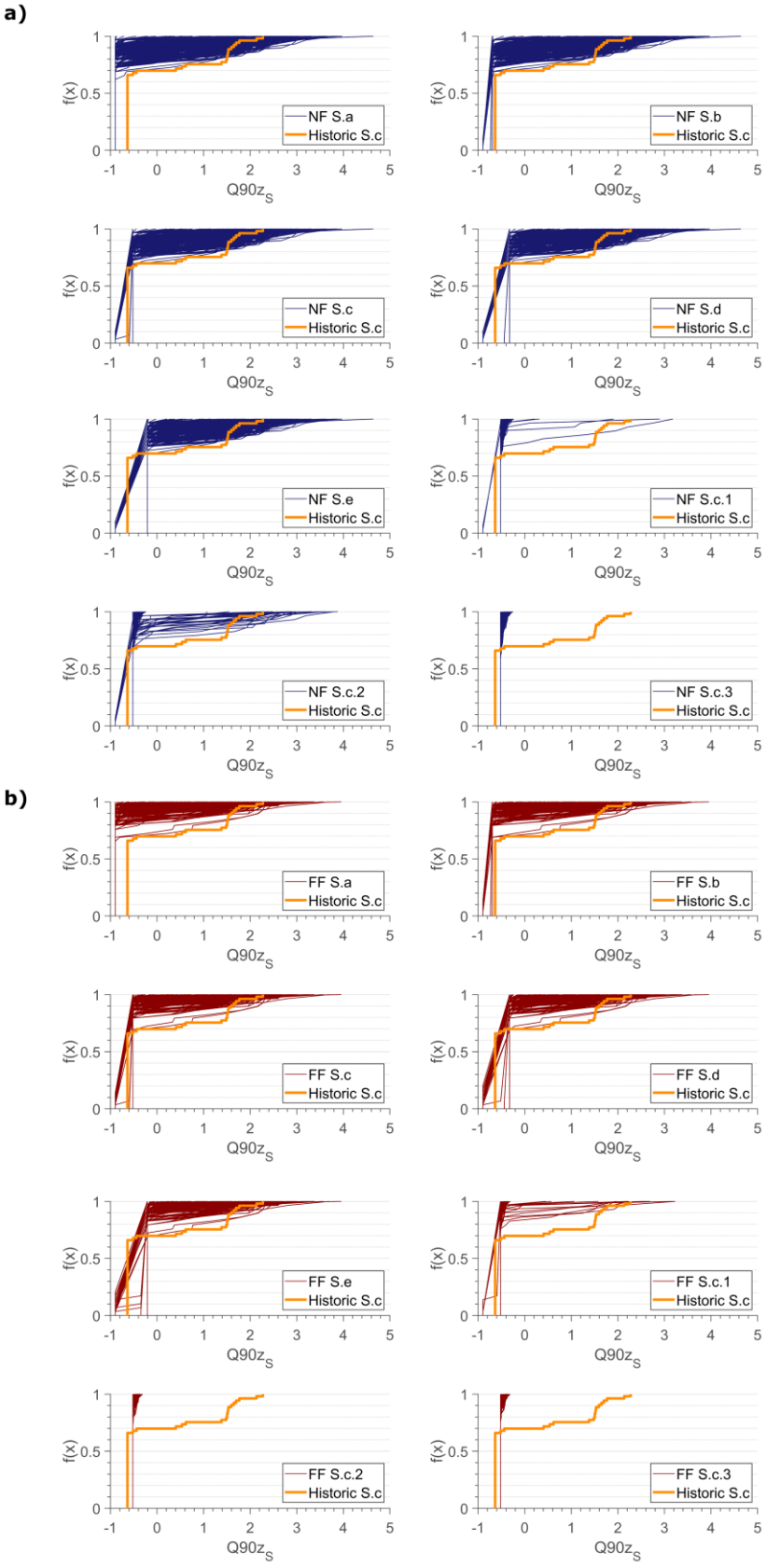
Supplementary Table 6.6. Simulated LIFE score statistics under Strategy S.c.

	Historic	**Baseline**	**Near Future**	**Far Future**
Maximum	7.04	7.47	7.48	7.34
Mean	6.46	6.35	6.32	6.30
Minimum	5.93	5.22	5.18	5.21
Standard Deviation	0.29	0.31	0.30	0.29

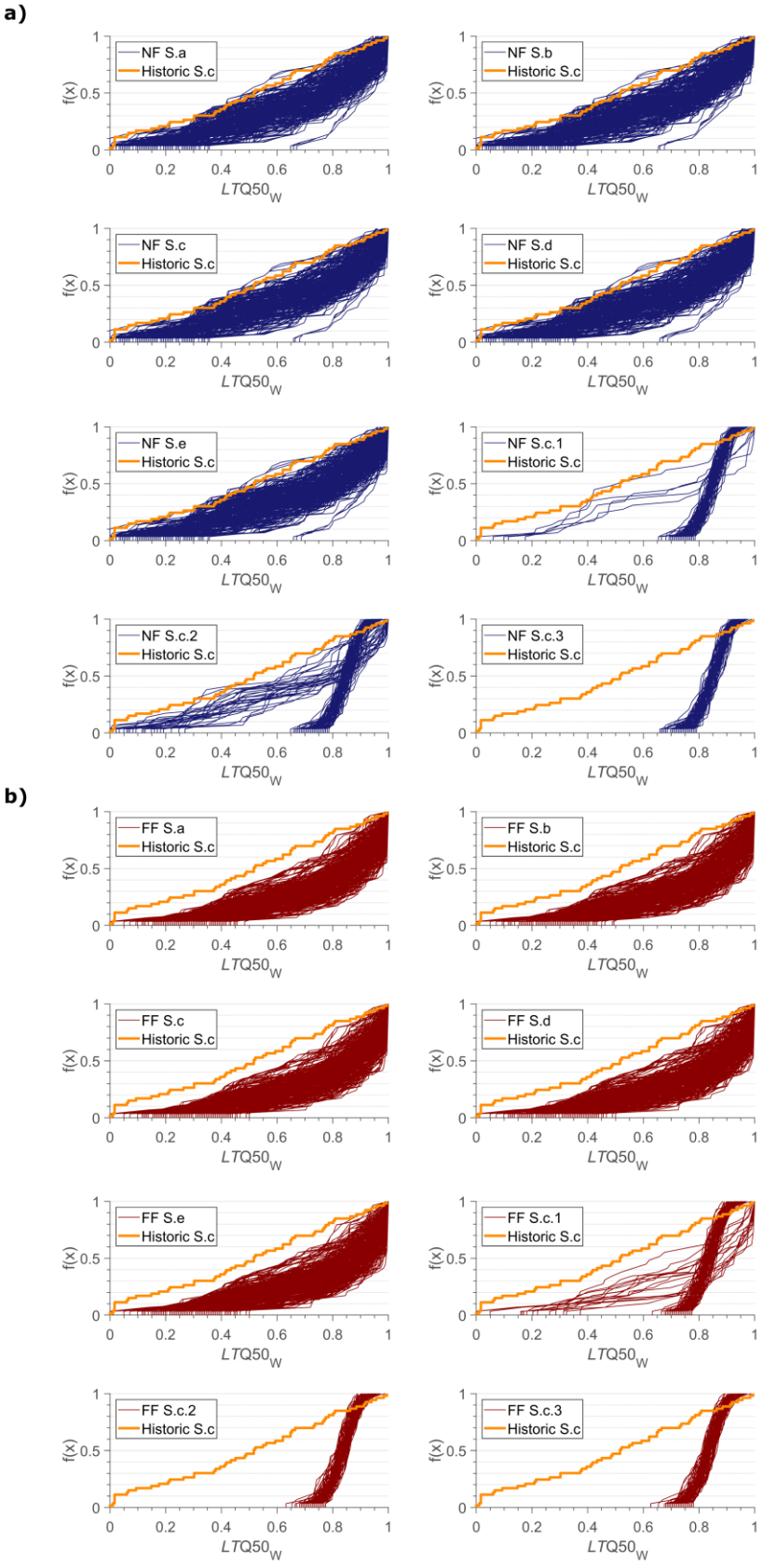
6.5.8 Appendix C8



Supplementary Figure 6.10. CDFs of $MTQ10_S$ along Arc M when simulated using regulation strategies for Historic, Near Future (**a**) and Far Future (**b**) periods.



Supplementary Figure 6.11. CDFs of simulated $Q90z_S$ along Arc M when simulated using regulation strategies for Historic, Near Future (**a**) and Far Future (**b**) periods.

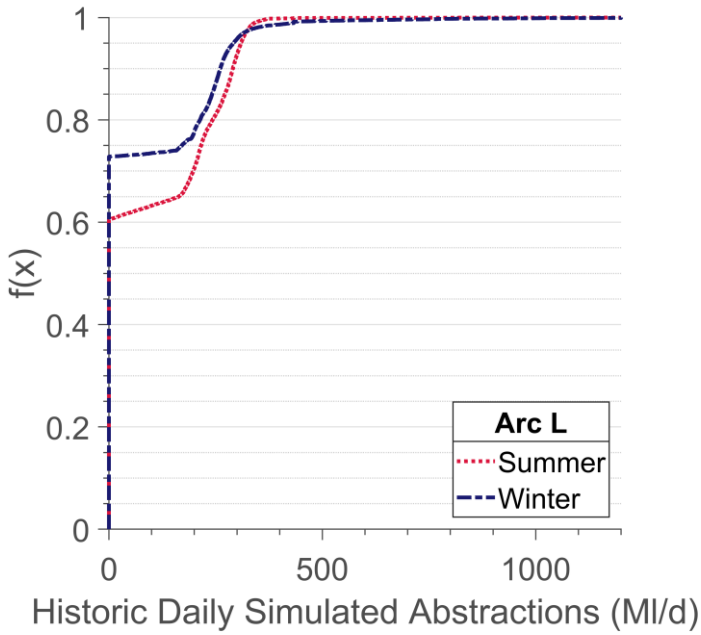


Supplementary Figure 6.12. CDFs of $LTQ50_W$ along Arc M when simulated using regulation strategies for Historic, Near Future (**a**) and Far Future (**b**) periods.

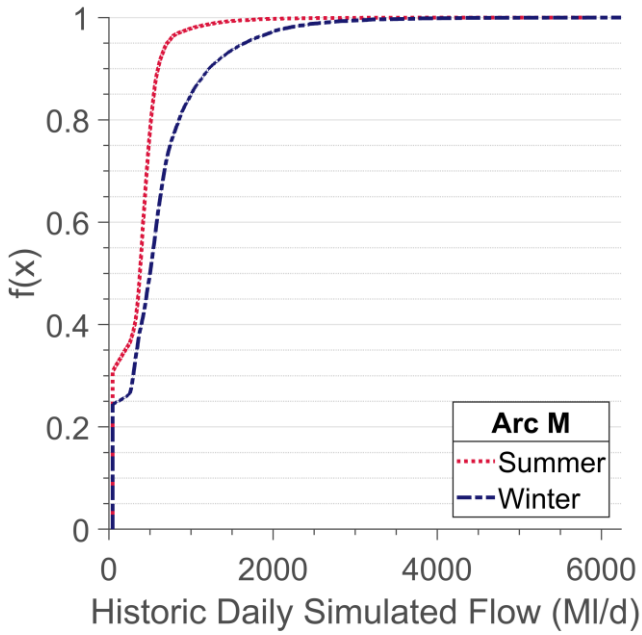
6.5.9 Appendix C9

In the simulation of historic conditions (1962-2015), withdrawal levels were set not to exceed the current licence (1200Ml/d), whilst also being constrained by the MRF. **Supplementary Figure 6.13** plots the distribution of daily withdrawal volumes along Arc L in summer and winter seasons. The curves indicate that (i) no water is withdrawn in at least 60% of days in either season, and (ii) water withdrawals greater than 350Ml/d occur in a small proportion of simulation days. This suggests that the current maximum daily water withdrawal licence rarely influences day-to-day withdrawals, with volumes more likely influenced by water availability in the river and other regulatory constraints in the system such as the MRF downstream (along Arc M). Whilst records of water withdrawals into the Lee reservoirs are not made publicly available, conversations with Thames Water confirmed that the abstraction volumes simulated in this study reflect their day-to-day withdrawals in the Lee, where licence volumes are much higher than what is actually taken. **Supplementary Figure 6.13** indicates that large decreases to the maximum daily withdrawal licence are necessary to influence day-to-day withdrawal volumes.

Supplementary Figure 6.14 presents the distribution of simulated daily flows along Arc M under historic conditions. The plots reveal that in less than 30% of days in each season flow along Arc M is equal to MRF threshold (45Ml/d).



Supplementary Figure 6.13. Distribution of simulated historic summer and winter daily withdrawal volume along Arc L.



Supplementary Figure 6.14. Distribution of simulated historic summer and winter daily flows along Arc M.

7 Conclusions

7.1 Thesis summary

The principal aim of this doctoral thesis has been to innovate and operationalise current water resource planning methodologies by advancing risk-based approaches to decision making under uncertainty. Three objectives were identified to achieve this aim: (i) to develop an adaptive risk-based planning methodology which uses uncertain climate and demand projections to identify optimal decision rules that inform water resources planning decisions; (ii) to investigate the vulnerability of water management planning options to spatially heterogeneous patterns of water demand and extreme synthetic climate events with characteristics not represented in the historical record, and examine how management decisions can be informed by extensive stress testing; and, (iii) to evaluate the role of river ecosystem health in informing water resource planning decisions under uncertainty. These objectives were achieved through three separate investigations which used the London urban water system and surrounding areas as a demonstrative case study. All three studies have been submitted to peer reviewed journals.

Chapter 2 presents a critical discussion of existing approaches for decision making under uncertainty, and outlines the challenges faced by decision makers planning for water security in the 21st Century. The chapter identifies three limitations of existing approaches, which align closely with the objectives listed in **Chapter 1**. **Chapter 3** outlines the modelling framework and data used in this thesis to address these limitations. Together, **Chapters 2** and **3** describe how simulation and optimization tools can be used alongside extensive hydro-climatic and socio-demographic data to inform multi-objective water resources planning, and successfully explore emerging trade-offs between adaptation cost, water supply reliability, and environmental health.

Chapter 4 targets limitation 1, presenting an indicator-based water planning framework that addresses key methodological challenges common to dynamic adaptive planning approaches. First, the framework identifies observable indicators that provide reliable information about current and future changes in the water system. The indicators must be germane to system performance and parsimoniously characterise non-stationary time series of sources of uncertainty. The selected indicators are monitored over time and used in threshold-based decision rules to determine if, when and what adaptation options are implemented in the water supply system. The threshold values in decision rules are specific to individual adaptation actions and are defined using multi-objective optimization techniques. The principal aim of the planning framework is to identify rule-based strategies that minimise (in a Pareto-optimal sense) (i) the financial costs of operating and adapting the water system, and (ii) the expected risk of water restrictions across a range of future conditions. The case study application illustrates the effectiveness of the framework in overcoming issues of mal-adaptation, using data-driven simulation techniques typical of risk- and robustness-based planning methods. By adopting rule-based planning strategies, water planners in the Thames Basin could achieve reductions in expected restriction costs of 13.1% on average for a given intervention cost. Overall, the results support the hypothesis that the performance of long-term adaptation plans can be improved by using observable indicators of change to inform decision making processes under sources of climate and demand uncertainty.

Chapter 5 focuses on limitation 2, examining the resilience of water supply infrastructure to spatially heterogeneous uncertainties in supply and demand. The chapter presents an integrated climate, hydrological and water resource modelling framework which is used to explore meteorological, hydrological, and water resource drought events afflicting neighbouring water systems, and explore how the spatial characteristics of these

droughts may change with different adaptation actions and operating arrangements. The research concentrates on the resilience of inter-basin transfer infrastructure, which is projected to be impacted by spatially coherent droughts spanning multiple water supply systems. The framework is used to examine proposed transfer infrastructure between the Severn and Thames Basins in South England. Results reveal that drought events will likely increase in frequency and intensity throughout the 21st Century. Simulation indicates that the new transfer has the capability to increase the resilience of water supplies to extreme dry periods, although its success varies under different operating agreements. The results illustrate the importance of testing adaptation infrastructure and operating policies against a wide range of hydro-climatic and socio-demographic conditions. In this case, the projections derived from Weather@Home weather sequences and DECIPHeR flow scenarios contain more extreme and spatially heterogeneous drought events than those represented in historical records, and so were ideal for examining infrastructure vulnerability to future climatic threats.

Chapter 6 presents a novel methodological framework that succeeds in promoting greater representation of environmental and regulatory uncertainties in water planning problems. Much like **Chapter 5**, this chapter uses simulation to test reductions to regulatory limits on river water withdrawals and downstream minimum flow requirements, helping to overcome real-world planning problems of balancing aquatic health against water supply in periods of high water stress. The framework draws on methods from environmental flow studies and risk-based water planning approaches, pairing empirical evidence of ecosystem condition and historical flow records with climate change driven future flow scenarios and demand projections. The case study example successfully simulates ecosystem response to future hydrological change, and shows how regulation can be moderated through the exploration of emerging trade-offs between water supply

and aquatic health. The case study application found that under the current regulatory policy, aquatic health along the Lee river will decrease throughout the 21st Century. Significant reductions to the existing withdrawal policy and downstream flow requirements are required to maintain aquatic health into the future, which will likely impact water supply to domestic water users if enacted. The results indicate that such reductions must be countered by adaptation interventions elsewhere in the water supply system, such as those discussed in **Chapters 4** and **5**.

7.2 Research contributions

The techniques presented in this thesis are designed to target specific uncertainties inherent to water resource systems planning and management, tackling issues arising from climate change, population growth, and environmental degradation. The principal contributions of the research presented in **Chapters 4**, **5** and **6** therefore take the form of methodological advancements, as summarised below:

i. A new methodology for long-term water resources planning is presented, which combines principles of risk-based decision making and dynamic adaptive planning. As established in **Chapter 2**, dynamic planning overcomes issues of uncertainty by generating adaptation policies that evolve as conditions are realised over time (Herman et al. 2020). Yet, existing methodologies are disjointed in their application and offer varied practical guidance for real world practitioners. Unlike previous studies, the step-by-step framework described in **Chapter 4** integrates linear regression, simulation, and optimization techniques to select observable indicators of change that best represent system performance over the future planning horizon. The proposed framework offers a powerful tool to help water

managers make risk-based adaptation decisions in the face of significant supply- and demand uncertainties.

ii. A framework is developed in **Chapter 5** to assess the vulnerability of adaptation infrastructure to a large ensemble of climate change driven future flows and demand projections. The research goes beyond existing climate impact studies which focus on uncertainties intrinsic to single water supply systems, analysing spatially dependent droughts on large scales and quantifying heterogeneous patterns of water use restrictions. The methodology allows water planners to analyse changing characteristics of meteorological and hydrological drought over time, and identify transfer arrangements that increase the resilience of inter-connected water supply systems to future drought events.

iii. A novel empirical analysis is presented in **Chapter 6** to quantify the impact of climate change and population driven changes in water demand on aquatic health. The systematic methodology is unique as it directly links empirical indicators of ecological condition and water system simulation output, offering practical guidance to water managers on how to balance water supply pressures and river health in an uncertain future.

iv. The research presented in this thesis illustrates the utility of risk-based approaches in water resources planning. The planning frameworks presented in **Chapters 4**, **5** and **6** effectively communicate observable outcomes related to adaptation cost, water system reliability, infrastructure vulnerability, and environmental change. The outcomes can be used by water planners to identify adaptation actions appropriate to their water system and risk preferences.

v. Finally, this research showcases the importance of using real-world observations *and* uncertain projections of climate change and water demand when planning

water resources. The thesis has demonstrated the usefulness of widely available climatological, hydrological, demographic, and environmental datasets, and showcased the applicability of numerous modelling platforms to water resource planning.

7.3 Practical applications

In addition to the research contributions, this thesis aimed to provide practical information for adaptive water resources planning of London's water supply system. Application of the three planning frameworks in **Chapters 4**, **5** and **6** yielded several planning recommendations for water planners and stakeholders, summarised below:

i. Traditional water planning approaches used by water agencies require the water planner to commit to long-term adaptation projections without knowing how future conditions will evolve. Whilst dynamic adaptive management is at the forefront of water planning discussions, no plans in England are fully adaptive. Current plans therefore have a high potential for financial regret if infrastructure is built in a future containing only mild changes to supply and demand. The rule-based planning framework presented in **Chapter 4** provides a convenient way to operationalise adaptive management, helping to reduce financial regret across a wide range of future conditions. Furthermore, the case study investigation reveals that statistics of low flow and annual water demand can be used to inform adaptation decisions in the Thames Basin.

ii. Results from **Chapter 5** indicate that streamflow and precipitation drought events will increase in frequency and severity throughout the 21st Century, having a detrimental impact on water supply reliability in the Thames Basin. The results presented in **Chapters 4** and **5** strongly advocate for the development of inter-basin

transfer infrastructure in Southern England to overcome this issue. The research shows that increased connectivity between geographically distinct water supply systems will enhance drought resilience and help water planners navigate increasing demand pressures.

iii. The case study investigation presented in **Chapter 6** reveals that existing water withdrawal policies in the Thames Basin could be adapted to better reflect changing ecosystem dynamics under 21st Century conditions. This chapter presents quantitative methods that use easily-accessible macroinvertebrate and river flow data, with the aim that the techniques can be adopted by water planners in England to support rigorous and risk-based policy reform.

7.4 Limitations and future research

Despite the methodological advancements made in this thesis, several opportunities exist to improve on the research presented here. This section identifies the key limitations of the thesis work and describes prospective directions for future research.

i. As with most decision-making approaches, it is difficult to address all sources of uncertainty inherent to water resources planning. In this thesis, the three planning frameworks presented in **Chapters 4**, **5** and **6** make simplistic modelling assumptions about the availability of groundwater supply under climate change. The assumptions are largely consistent with other water resource planning approaches applied to the Thames Basin, which either: (i) do not model changes in groundwater storage and output (Borgomeo et al. 2014, 2018, 2016); or, (ii) model groundwater by aggregating water supply boreholes to one abstraction point per basin (Huskova et al. 2016). Whilst groundwater has been widely researched in the hydrological community, it has received less attention in the water resources

planning community. Future work should seek to improve estimations of groundwater yields for individual borehole sources, and develop quantitative methodologies to evaluate the resilience of existing and new groundwater infrastructure to 21st Century climate conditions. For example, the groundwater model described in Dobson et al. (2020) could be integrated in the planning framework presented in **Chapter 5** to inform management of existing water supply boreholes and prevent over-use during drought events. In addition, statistics of past and current groundwater levels could be considered as observable indicators in the framework presented in **Chapter 4**, provided they are suitably represented in the simulation framework. Groundwater indicators may prove especially useful for predicting future risk of water shortages in water supply systems that rely heavily on groundwater supplies, or in basins with groundwater-fed rivers.

ii. This thesis assumes that the quality of surface water supplies is acceptable if regulatory constraints (i.e. minimum flow requirements) are satisfied in simulation. However, water quality assessments in UK catchments have shown that future climate and land-use change may enhance algal blooms and eutrophication (Whitehead et al. 2013), and increase dissolved organic carbon in river networks (Lee et al. 2020). New supply infrastructure could also impact river conditions. Transfer infrastructure, for example**,** is likely to modify the colour, turbidity, and composition of suspended solids in the river network, as well as alter the concentration of metaldehyde, individual and combined pesticides, phosphates, ammonia, nitrate and nitrite, pathogens, and bromide (Thames Water, 2015). Development of a coupled water quality-quantity modelling framework, like the framework presented in Mortazavi-Naeini et al. (2019), would enhance the methods presented in this thesis by providing a mechanism to quantify water

quality risks under uncertainty. Importantly, development of coupled water-quality and quantity decision making tools would help to identify adaptation solutions that ensure reliable *and* potable water supply.

iii. As identified in **Chapter 2**, hydrological uncertainty presents a significant challenge to water planners. Whilst the planning frameworks outlined in this thesis provide the building blocks to assess for hydrological modelling uncertainty in water planning problems, the case study examples fail to consider uncertainty associated with hydrological model parameterisation. Instead, the three investigations use the best parameter sets for individual catchments in the Thames and Severn Basins, as identified in work by Coxon et al. (2019) and Dobson et al. (2020). Scenario discovery (McPhail et al. 2020) and sensitivity analysis (Pianosi et al. 2016) would complement efforts to improve the representation of hydrological uncertainty in the proposed planning frameworks, with future work exploring the effect of hydrological model parameter uncertainty on water system performance, drought resilience, and assessments of aquatic health.

iv. **Chapter 5** is limited by its assessment of the resilience of inter-basin transfer infrastructure between two cooperative neighbouring supply systems. It has been widely documented that trans-boundary water resources management can be complicated by political barriers and conflict over riparian rights (Gupta & van der Zaag, 2008; Lund & Israel, 1995b; Wheeler et al. 2018). Applications of the framework presented in **Chapter 5** should be mindful of this fact, and where necessary, ensure that political and social uncertainties are represented in the modelling process. Because these sources of uncertainty may be difficult to sample or characterise (Herman et al. 2020), future work should focus on developing modelling frameworks that better represent hydro-climatic forcing *and* human

behaviour. Agent-based simulation (Giuliani et al. 2016) or dynamical systems modelling (Di Baldassarre et al. 2016), for example, may help to capture key human-water interactions under competing adaptation actions and uncertainties.

v. Finally, further validation is required to ensure that the three planning frameworks presented in this thesis are appropriate for water systems outside the UK. The proposed methodologies should be replicable for other water supply systems, provided the data required for each assessment are available. Admittedly, data availability presents a significant barrier in application of the planning frameworks. Future research should aim to increase the suitability of the proposed methods to data scarce regions. In regions with limited ground observations, this could be achieved through bottom-up approaches for data-collection (Conway et al. 2019). For example, Community Based Monitoring (or citizen science) has helped to expand hydro-climate records in several catchments across Ethiopia, and in due course, improve understanding of water availability and watershed behaviour (Walker et al. 2019a; Walker et al. 2019b). Above all, future work should ensure that the underlying themes of this thesis, principally climate resilience, water supply reliability, and environmental protection, remain at the forefront of adaptive water resources planning under uncertainty.

7.5 Concluding remarks

Developing adaptive water resources plans that are resilient to climate change, demand growth, and environmental change is a challenging task. In the Thames Basin, increases in climate related risks and population driven demand growth have amplified pressures on the existing water supply system. This thesis describes three distinct planning frameworks that help to identify adaptation actions that will alleviate these pressures. The findings

underline the importance of careful planning, with new supply infrastructure and revised regulatory policies offering distinct trade-offs in climate risk reduction, cost, resilience, and environmental protection. The research outputs illustrate the benefit of systematically planning for hydro-climatic, environmental, and socio-demographic uncertainties, communicating important outcomes of interest to water planners. Whilst the research focusses on adaptation in the Thames Basin, the principles underpinning the proposed frameworks are relevant for other water resources systems facing future supply and demand uncertainties. Ultimately, it is hoped that the methods presented in this thesis provide guidance for water planners working to secure long-term public water supply.

Appendix D: Co-author paper contribution statements

To the Director of Graduate Studies,
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Environmental Change Institute
South Parks Road, Oxford OX1 3QY

I, Jim W. Hall, certify that Anna Murgatroyd completed the majority of the work in each of the chapters that form part of their DPhil thesis, as well as any associated articles that have already been published or may be published in the near future.

Signature:



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Date: 4 January 2020

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