ADAPTATION PLANNING UNDER CLIMATE CHANGE UNCERTAINTY

Using Multi-Criteria Robust Decision Analysis in a Water Resource System

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The candidate confirms that the work submitted is her own and that appropriate credit has been given where reference has been made to the work of others.

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For any errors or inadequacies that may remain in this work, of course, the responsibility is entirely my own.

Abstract

This project explores the uncertainty factors in drought planning for a water resource zone in Sussex. Nine planning options from the 2009 Sussex Water Resource Management Plan were assessed using four climate products: the 2009 UK Climate Projections Change Factors, the Spatial Coherent Projections, the 11 runs of the HadRM3 regional climate model and their subsequent downscaling by the Future Flows Project. The varying drought statistics from these four climate products reflect post-processing uncertainty - the uncertainty stemming from the process of converting original climate model outputs into products of different formats, variables and temporal/spatial scales. Overall, the study has integrated a cascade analysis of climate uncertainty, climate post-processing uncertainty, hydrological uncertainty, water resource model uncertainty and demand uncertainty on water resource planning. The study combines Robust Optimisation, Decision-Scaling and Robust Decision Making into Robust Decision Analysis, a decision making framework for dynamic adaptation pathways in response to different levels of uncertainty and risk averseness. Post-processing uncertainty is the dominate uncertainty until 2030s; 2050s is then dominated by demand and socio-economic uncertainty. The most severe droughts within the Spatial Coherent Projections and the 2009 UK Climate Projection products are variations of the 1975-1976 and the 1988-1989 droughts, two of the worst historic droughts currently used as the design events for drought planning in Sussex. The system appears to be robust to variations of these past droughts. Yet, under different sequences of droughts from the HadRM3 and Future Flows products, the system demonstrated frequent supply failures in the 2050s, unless water demand is maintained at the 2007 level or lower. While operational costs in the 2030s are generally within the region of 4 to 5 million GBP per year, those in the 2050s Market Forces jumped to the region of 5 to 15 million GBP per year and with supply deficit from 0 to 1100 Ml/year. When demand grows by 35% from the 2007 baseline level, universal metering becomes a key option. Despite climate post-processing uncertainty, the main hotspots of water deficits remains similar across the climate products and are driven by network bottle-necks and the continually high dependence of the system on water sources around the Hardham area. The study also indicates that inter-regional transfers might not be as reliable as assumed.

Keywords: water resource planning, robust decision analysis, multi-criteria, adaptation, climate products

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List of Key Abbreviations

AMP	*Asset Management Plan*
ASR	*Aquifer Storage Recharge*
AQUASIM	*Aqua Simulation Model*
CAPEX	*One-off capital investment cost*
CATCHMOD	*Catchment Model*
CC	*Consumer Council*
CCDEW	*The Climate Change and Demand for Water*
CEH	*Centre for Ecology and Hydrology*
DEFRA	*The Department for Environment, Food and Rural Affairs*
Dos	*Deployable Outputs*
DP	*The Direct Percolation*
EA	*The Environment Agency for England and Wales*
FF	*Future Flow*
FAO	*Food and Agriculture Organisation*
FRS	*Family Resource Survey*
GAMS	*Generalised Algebraic Modelling Software*
GCMs	*Global Climate Models*
GLUE	*The Generalised Likelihood Uncertainty Estimation*
GW	*Groundwater*
HadRM3	*Hadley Centre Regional Climate Model*
I	*Innovation*
IPCC	*The Intergovernmental Panel for Climate Change*
IRAS	*Interactive River-Aquifer Simulation*

LP/DP	*Linear or Dynamic programming*
LR	*Local Resilience*
MF	*Market Forces*
MOREC	*The Meteorological Office Rainfall and Evaporation Calculation system*
MOSES	*The Meteorological Office Surface Exchange Scheme*
MRF	*Minimum Residual Flow*
MRFWW	*Weirwood Minimal Residual Flow*
MRSE	*The Mean Squared Residual of Errors*
MSE	*The Mean Squared Errors*
NPV	*Net Present Value*
OFWAT	*The Water Services Regulation Authority*
OPEX	*Operational cost*
PCC	*Per Capita Consumption*
PDSI	*Palmer Drought Severity Index*
PET	*Potential Evapotranspiration*
PPE	*Perturbed Physics Ensembles*
Q90	*The 90th percentile of daily flows*
RCM	*Regional Climate Model*
RDM	*Robust Decision Making*
SAI	*Standardised Anomaly Index*
SB	*Sustainable Behaviour*
SCPs	*The Spatially Coherent Projections*
SDB	*Supply Demand Balance*
SEW	*South East Water*
SPEI	*The Standardised Precipitation- Evapotranspiration Index*

SPI	*The Standardised Precipitation Index*
SRES	*The Special Report on Emissions Scenarios*
SREX	*Special Report on Managing the Risks of Extreme Events and Disasters*
SW	*Southern Water*
UKCIP	*United Kingdom Climate Impact Program*
UKCP	*The United Kingdom Climate Projections*
UKWIR	*The United Kingdom Water Industry Research*
VBA	*Visual Basic Application*
WBM	*The Water Balance Model*
WSW	*Water Supply Work*

Chapter 1. INTRODUCTION

Climate change and its subsequent impacts on water resources can affect many aspects of society and the environment. This is not new. Many early human civilisations started and revolved around rivers such as the Nile, the Tigris-Euphrates, the Indus and the Yellow River; many more flourished or failed due to their capacity to manage and share these water resources (Sadoff and Grey, 2002). The potential changes in water availability have become a problem for water management and decision making across both spatial and temporal scales.

Adaptation has become one of the major strategies to cope with climate change. While adapting to natural changes has been an integral part of the human activities, the advent of climate change and its impacts can potentially require unprecedented and widespread adjustments. The last three decades have witnessed a remarkable but gradual shift in our attitude to the risks of climate change and their subsequent impacts. Back in 1977, the US Panel on Water and Climate (1977) asserted only a "*small probability of a change in regional climate so abrupt, widespread, severe, and statistically unambiguous that current water resource design practices need or should be radically altered...*". Mitigation was viewed as the main response and the risk was not considered to be pressing for immediate actions. Thirty years later, numerous studies indicated that we are indeed living in a changing climate (Parry et al., 2007; Bellard et al., 2012; Doney et al., 2012; Arnell and Gosling, 2013). Adaptation appears to be an inevitable option due to the level of uncertainty surrounding the change (Salinger, 2005; Moreira et al., 2007). Hallegatte et al. (2012) described this level of uncertainty as **deep uncertainty**, "*a situation in which analysts do not know or cannot agree on (1) models that relate key forces that shape the future, (2) probability distributions of key variables and parameters in these models, and/or (3) the value of alternative outcomes*" [p.2].

Uncertainty persists from climate projections to subsequent 'knock-on' effects on the ecosystem, the hydrosphere, biosphere and the human societies. In the face of such explosion of uncertainty (Wilby and Dessai), there have been concerns about the inadequacy of the current water management practices regarding water supply reliability, flood risk, health, energy and aquatic ecosystems (Kundzewicz et al., 2008; Minville et al., 2010). The need to move away from the *status quo*, to adapt and revisit management policies, as such, is urgent and challenging (Fankhauser et al., 1999; Adger, 2003; Stern, 2007).

1.1.WHAT ARE THE KEY FACTORS TO ADAPTATION SUCCESS?

1.1.1. Why adapt and what is adaptation success?

Yet, what constitutes adaptation and the factors of adaptation success are still far from clear. In the context of the water industry, these issues represent major challenges in current and future planning. Smithers and Smit (1997) have shown several conceptual foundations of adaptation. Ecological adaptation refers to the reactive responses and genetic evolution of a species. On the contrary, adaptation in social sciences emphasises planning and decision making that go beyond species survival. This study follows the adaptation definition of The Intergovernmental Panel for Climate Change (IPCC)'s Special Report on Managing the Risks of Extreme Events and Disasters (SREX), which defines adaptation as adjustments in human systems to changes in climatic stimuli (Field et al., 2012). Translating these types of adaptation into the climate change context, adaptation has been classified into three categories: *autonomous* (passive and spontaneous adaptation to existing changes), *planned* (based on an awareness of historic or near-future changes), *anticipatory* (actions before observed impacts of changes) (proactive adaptation) (McCarthy, 2001). Adaptation can further be described as a process of moving from sustaining *status quo* (*resilience)* to incremental change (*transition*) and paradigm shift (*transformation*) (Pelling, 2011). Smit et al. (2000), meanwhile, characterised adaptation by the goals (adapt to what?), the actors (who or what adapts) and the process (how it occurs).

The focus of adaptation is also increasingly placed on enhancing adaptive capacity instead of specific adaptation measures (Smit and Pilifosova, 2003). Adaptation success has been linked to various criteria, including the absence of vulnerability, robustness, resilience (Smit et al., 2000; Füssel and Klein, 2006), flexibility (Fankhauser et al., 1999), effectiveness, efficiency, equity and legitimacy (Adger et al., 2005; Paavola and Adger, 2006) (Table 1-1). Adaptation success, however, may not transmit across scales and criteria and therefore should be assessed at different scales (Adger et al., 2005).

Table 1-1 Definitions of adaptation characteristics in Adger et al. (2005), Smit et al. (2000)

Characteristics	Description
Sensitivity	Degree to which a system is affected by, or responsive to, climate stimuli
Susceptibility	Degree to which a system is open, liable or sensitive to climate stimuli (similar to sensitivity, with some connotations toward damage)
Vulnerability	Degree to which a system is susceptible to injury, damage, or harm (one part-detrimental-of sensitivity)
Impact Potential	Degree to which a system is sensitive or susceptible to climate stimuli
Stability	Degree to which a system is not easily moved or modified
Robustness	Strength; degree to which a system is not given to influence
Resilience	Degree to which a system rebounds, recoups or recovers from a stimulus
Resistance	Degree to which a system opposes or prevents an effect of a stimulus
Flexibility	Degree to which a system is pliable or compliant (similar to adaptability, but more absolute than relative)
Coping Ability	Degree to which a system can successfully grapple with a stimulus (similar to adaptability, but includes more than adaptive means of "grappling")
Responsiveness	Degree to which a system reacts to stimuli (broader than coping ability because responses need not be "successful")
Adaptive Capacity	The potential or capability of a system to adapt to (to alter to better suit) climatic stimuli
Adaptability	The ability, competency or capacity of a system to adapt to (to alter to better suit) climatic stimuli
Effectiveness	The capacity of an adaptation action to achieve its expressed objectives
Efficiency	Consideration of the distribution of the costs and benefits of the actions; the costs and benefits of changes in those goods that cannot be expressed in market values; and the timing on adaptation actions

Equity	Identifying who gains and who loses from any impact or adaptation policy decision
Legitimacy	The extent to which decisions are acceptable to participants and non-participants that are affected by those decisions

1.1.2. Robustness, resilience and vulnerability: why are they relevant to the issue of adaptation

In characterising adaptation success, the concepts of robustness (Wilby and Dessai; Lempert and Schlesinger, 2000; Dessai, 2005), resilience (Fowler et al., 2003; Hughes et al., 2003; Tompkins and Adger, 2004; Adger et al., 2007; Pahl-Wostl et al., 2007) and vulnerability (Vörösmarty et al., 2000; Füssel and Klein, 2006; Williamson et al., 2012) have been frequently mentioned. Robustness, reliability, resilience and vulnerability appear to be the key characterising elements of water resource planning performance (Hashimoto, 1980). Similar to the concept of adaptation, there is also a conceptual dichotomy between the natural sciences and socio-ecological definitions of these terms. In particular, engineering robustness (Hashimoto, 1980) refers to the sustenance of system performance amidst perturbation and uncertainty (Anderies et al., 2004) while planning robustness indicates the flexibility to switch plan (Rosenhead et al., 1972). Meanwhile, engineering resilience (Hashimoto, 1980) is the recovery time to the prior-collapse state and ecological resilience is the amount of disturbance that a system can absorb without losing its core processes and structures (Holling, 1996; Folke, 2006). Similarly, vulnerability could either be viewed as the 'end point' in a 'top down' climate impact assessment approach, or the starting point determining local adaptive capacity in a 'bottom up' approach (O'Brien et al., 2009). The dichotomy of these concepts reflects two alternative views on adaptation: as actions to preserve the current state and as a process of transformation in response to internal stress and climatic stimuli. Furthermore, the engineering approach assumes a single equilibrium that the system should revert to, while the socio-ecological approach allows multiple stable system states. Nevertheless, both of these approaches are relevant in the adaptation context: within a certain coping range, a system should be able to resist disturbances and recover to its normal functional state; however, a system should also accommodate system transformation in response to changes. As such, there is a need to integrate the socio-ecological aspects of adaptation and its characteristics into the engineering approach. This study acknowledges both sides of these concepts and defines the overall **robustness** as the system capacity to resist disturbances while maintaining planning flexibility amidst uncertainty. **Resilience** is defined as the capacity to regain system functions after disturbance and **vulnerability** is the risk of system collapses due to both climatic stimuli and internal system attributes.

In the face of uncertainty, **robustness** is a highly relevant concept to adaptation in water resource planning. The practice of water resource planning has long relied on the natural water balance and the seasonal cycle of water supply. Yet, a non-stationary climate requires fundamental revision and renovation of such practice (Milly et al., 2008). Climate uncertainty appears to be the dominant uncertainty factor on hydrological response (Arnell, 1999b; Wilby, 2005; Kay et al., 2009), although the effects are likely to be catchment-dependent (Boorman and Sefton, 1997).The effects of climate change on water resources are evident in various catchments and water systems (Leavesley, 1994; Vörösmarty et al., 2000; Werritty, 2002; Brekke et al., 2004; Wilby et al., 2006; Dessai and Hulme, 2007; Fowler et al., 2007). Water resource systems are sensitive to changes in both moderate and extreme climate variation (Němec and Schaake, 1982). Therefore the impacts of these changes on the systems and the decision making process should be considered.

Nevertheless, integrated studies on how climate uncertainty propagates from the climate projections to the decision making scale, especially when coupled with hydrological and socio-economic uncertainty, are sparse. Some examples of studies within that stream include Dessai and Hulme (2007), Lopez et al. (2009a), Ranger et al. (2010) , Darch et al. (2011) and Matrosov et al. (2012). To date, there have been few studies that demonstrate the uncertainty the decision makers face, in particular with regards to different climate information from different sources and how selecting the information might affect their decisions. This issue is vital and relevant to decision making in practice. Furthermore, water resource planning also needs to consider other stressors such as demand growth and its associating potential risks. The direct effects of climate change such as the exacerbation of droughts and floods could further interact with existing demand pressure and lead to other indirect effects of excessive groundwater abstraction and extra demand pressure (IPCC, 2007). As such, there is a need for an integrated assessment that includes the relevant uncertainty factors, analyses their influences on the planning process and identifies potential robust strategies under such uncertainty.

1.2. RESEARCH QUESTIONS, AIMS AND OBJECTIVES

Further research into how climate uncertainty could affect adaptation decisions is important and essential. Practitioners such as water managers are currently incorporating complex climate projections into decision making and need to consider the role of uncertainty in robust adaptation decisions. Yet climate projections are subject to deep uncertainties and such uncertainties could cascade into water resource planning. Furthermore, the overall implications of climate changes are intertwined with intricate socio-economic changes, leading to even more uncertain conditions. The research therefore addresses two key questions:

i) How does climate uncertainty in conjunction with impact modelling and socio-economic uncertainty affect drought planning decisions in water resource systems?

ii) Can the different criteria to robustness in adaptation decision be integrated and analysed to inform robust adaptation planning?

The study aims to explore the components in the uncertainty cascade from climate projections, hydrological modelling, water resource modelling and option identification. It limits its scope to climate change impacts on surface water and focuses on the water quantity aspect of drought planning. The objectives of the research are to:

i) Review different definitions and approaches of the concept of robustness in water resource planning: different approaches and definitions of robustness can guide the adaptation decisions towards different goals. This objective addresses the different underlying ideology of each approach and constructs a framework that engages the role of each approach.

ii) Construct a methodology and water resource models for a case study in south-east England that incorporates the main aspects of the robustness concept: The case study serves as an example of how robust adaptation decisions can be identified in practice. Furthermore it demonstrates how real-life decision making could incorporate climate change uncertainty along with socio-economic uncertainty.

iii) **Use robust decision making to demonstrate how the uncertainty components could affect the performance of adaptation options:** While being designed under the robustness framework, adaptation options could still be susceptible to changes in assumptions and uncertainty bounds. This explores the varying robustness of adaptation options under different factors and levels of uncertainty.

1.3.THESIS OUTLINE

Chapter 2 Literature Review reviews the key approaches to robustness and their associated criteria. It compares and contrasts Robust Optimisation, Real Option analysis, Info-gap Decision Theory and Robust Decision Making. It also presents a linking decision framework that emphasises the utility of these methodologies in reiterative planning cycles.

Chapter 3 Methodology describes the study framework to analyse uncertainty propagation and potential adaptation pathways that balance vulnerability and financial costs. It links elements of the uncertainty cascade and combines multi-criteria analysis with scenario planning to assess the overall impacts of uncertainty on drought planning options.

Chapter 4 Study Area describes the study area and adaptation context in details. It highlights the local relevant features to adaptation and outlines the steps of the subsequent assessments in Chapter 5 to Chapter 8.

Chapter 5 Climate Uncertainty explains the key characteristics of four climate products: the original Regional Climate Model HadRM3 ensembles, their downscaled projections produced by the Future Flows project, the UK Climate Program Spatial Coherent Projections (SCP) and the 2009 UK Climate

Projections (UKCP09) full set of 10,000 realisations. It analyses two uncertainty factors: the climate uncertainty represented by each of these products, and the uncertainty from the post-processing procedure that produces these products.

Chapter 6 Hydrological Uncertainty compares the climate uncertainty with the Generalised Likelihood Uncertainty Estimation (GLUE) of hydrological uncertainty. The chapter also employs Sobol-sensitivity analysis to explore parameter interaction under different flow conditions.

Chapter 7 Vulnerability Analysis examines the capacity of the current water resource system to cope with projected future changes in the 2020s, 2030s and 2050s. Considered uncertainty factors include climate uncertainty, post-processing uncertainty and socio-economic uncertainty. The chapter uses a simulation model and an optimisation model to produce vulnerability results as well as identify the severe drought years in each climate product.

Chapter 8 Option Analysis continues to assess the coping capacity of the system and potential options under deep uncertainty. The Chapter uses the Optimisation Model to identify packages of robust measures and the Simulation Model to test their performance under all planning scenarios. It also explores the cascaded uncertainty from the climate component and the different impacts projections due to using different climate products.

Chapter 9 Robust Adaptation Pathway Discussion revisits the aspects of robustness discussed in Chapter 2 and connects the findings with that theoretical framework. It analyses the robustness of the case study system to climate uncertainty, post-processing uncertainty, changing inflows, varying supply reliability and alternative socio-economic scenarios. It also assesses the system under the lens of planning robustness and plan switches. Finally it examines the assumptions and social uncertainty that could not be included in the modelling process.

Chapter 10 Conclusion summarises the all findings in views of the objectives laid out at the onset of the thesis. It reviews remaining limitations and presents recommendations for further research.

Chapter 2. LITERATURE REVIEW

2.1.INTRODUCTION

A certain amount of climate change is now unavoidable and requires timely adaptation decisions in water resource planning. Yet, projections of local climate change impacts are plagued with substantial unknowns, which make anticipatory adaptation difficult. As the climate is shifting, so are stream flows, occurrence of extreme events, and subsequently, the practice of water modelling and management (Arnell et al., 2001; Milly et al., 2008; Hirschboeck, 2009; Lins and Cohn, 2011; Peel and Blöschl, 2011). While non-stationarity in the climate and particularly the hydrological cycle is not essentially a new issue, climate change impacts emphasise the need to reconsider and incorporate principles of risk aversion and adaptation into water resources systems (Lins and Cohn, 2011). The risk introduced by climate change impacts has a wide range and high level of uncertainty, which frequently prompts the term "*deep uncertainty*" (Lempert and Groves, 2010). By definition, *uncertainty* is imprecise knowledge about the probability, distribution of events and the magnitude of their consequences on vulnerable receptors (Knight, 1921). *Deep uncertainty*, a subcategory, lies at the fuzzier end of *uncertainty,* where the direction and magnitude of changes are completely unknown (Bammer and Smithson, 2008). The capacity to maintain performance amidst uncertainty (also known as robustness) (Lempert and Schlesinger, 2000; Dessai, 2005) and the ability to absorb such disturbance (resilience) (Janssen and Anderies, 2007; Ben-Tal et al., 2009) has thus been increasingly used to assess water-resource systems.

Despite its analytical importance, robustness and its attributes have not been consistently defined in the literature of water resource planning. This ambiguity in terminology has been noticed in various documents concerning climate change impacts. For instance, in response to the 2006 draft report on climate decision making by the US Climate Change Science Program (Bertsimas et al., 2010), the review committee of the US National Research Council found the concept of robustness "insufficiently defined" (Ben-Tal and Nemirovski, 2002). Similarly, the Water Resources Planning Guideline by the Environment Agency for England and Wales (Environment Agency, 2012) stated robustness as a key requirement, yet, without any formal definition of the term.

The various definitions of "*robustness*" in current water resources planning can often be traced back to operational research, managerial science, statistics and control theory. These alternative paradigms underline various aspects and underlying philosophies which may or may not have been translated into water resource planning. In order to conceptualise the linkages and contrasts of these paradigms, this chapter presents a framework linking and highlighting the utility of these concepts for adaptation to climate change.

2.2. WHY ROBUST WATER RESOURCES SYSTEMS ARE NEEDED IN A CHANGING CLIMATE?

2.2.1. Water resources planning as a decision analysis problem

Water resource planning relies on the knowledge of water allocation over space and time. Water plans are often formulated as an optimisation problem, constrained by water availability and cost (Fiering, 1976). This approach maps the field into the domain of linear and dynamic programming, similar to what Bellman (1956) described as a decision under uncertainty. Most often, options are characterised as discrete solutions that entail one single action, such as to build a reservoir, to reduce leakage or to enhance the capacity of the water distribution network. When several options are employed in a plan, they are termed a portfolio of options, which also details the sequence of option implementation. Decision options in water resource planning largely reflect optimisation strategies toward designed conditions. For instance, the water system might be designed to cope with the worst historic droughts or floods (worst-case scenarios), on average flow conditions, or so that systems regain their pre-disaster performance within a certain period.

Whilst decision theories have been of assistance to water resources planning, particularly in the face of uncertainty, many of their key assumptions are not necessarily applicable in the context of deep uncertainty. Many traditional decision theories originated from betting games and function with the ideology of finding an optimal solution (Pahl-Wostl, 2002). Meanwhile, adaptation often emphasizes flexibility and a satisfactory level of system performance rather than solely an optimal behaviour of the system (Fankhauser et al., 1999). In some cases, water managers might apply hedging rules and devise the reservoir operation rules based on optimisation search techniques and assumptions of shortage probability (Shiau and Lee, 2005; Tu et al., 2008).

However, water resource planning is fundamentally a risk-averse industry, particularly when such hedging strategies may be prone to failure if the operating conditions deviate from the design conditions. Risk averse behaviour is typically the case when rewards for correct decisions are far less than punishment for system failures, similar to what Bell (1982) explained in his “regret theory” or minimax principle, in which people minimise the potential for loss (Morgenstern and Von Neumann, 1947; Parmigiani and Inoue, 2009). It appears that with highly risky activities, decision-making gravitates towards reducing the risk of wrong decision rather than outcome optimisation (Maguire and Albright, 2005). Various studies in decision theory and behavioural research have examined and attempted to prescriptively correct this “bias” (Von Winterfeldt and Edwards, 1986; Bell et al., 1988).

On the other hand, other decision theories stem from the recognition that such risk-averse behaviour in order to be safeguarded against risks and uncertainty is a legitimate choice. One of the earliest theories proposed was from Herbert Simon (1979), who uses “satisficing”, the notion of non-optimal but acceptable solutions, as an objective instead of utility functions and the “prospect theory” of Kahneman and Tversky (1979), who argue that decision makers base their decision on marginal gains and losses of each decision implementation to reach an acceptable level of utility. Alternatively, Rosenhead et al. (1972) constructed an approach that values the number of choices remaining after each decision compared with the number available at the prior-decision stage as a robustness criteria. Such an approach is often termed a "robust option", or a safe option under most circumstances being considered. The utility optimisation literature also uses this term to refer to an optimal option, such as one selected from Monte-Carlo sampling.

2.2.2. Towards robust water resources system in a changing climate: What is lacking?

Yet, as the climate is shifting, these future conditions become dynamic and uncertain. In most cases, there are uncertainties involved in the decision making process, not only in climate projections but also within hydrological and socio-economic ones (Kjeldsen and Rosbjerg, 2004; New et al., 2007; Stainforth et al., 2007b). The practice of option appraisal based on the *status quo* is now required to evolve with the system and its operating conditions. Adaptation responses in the face of uncertainty are grouped by Walker et al. (2013) into resistance (worst-case planning), resilience (recovery-based planning), static robustness (wide-range planning) and dynamic robustness (flexibility-based planning). The concept of robustness, as an enhancement to existing decision analysis, is important in formulating option selections and adaptation scenarios. Furthermore, it is also a key concept to systems under multiple types of disturbance and uncertainty, as robust options for particular types of disturbances may leave the system vulnerable to other types of disturbances, thus exacerbating these vulnerabilities (Janssen and Anderies, 2007).

Hitherto, current guidelines and requirements of robust adaptation options in water planning often stress static robustness; for instance, the guideline on water management plans in England and Wales (Environment Agency, 2012) requires water companies to demonstrate the feasibility and performance of their plans and options over the period of next 25-years without the need to analyse system flexibility via option switching. Consequently, legislation and institutional changes are needed to facilitate the adoption of criteria concerning option flexibility. The current literature on water resources planning also displays an emphasis on static robustness, namely by ensuring the option is sound cost and performance wise (Lempert et al., 2003; Hine and Hall, 2010).

On the other hand, adaptation revolving around flexible pathways and diversifying strategies prevails in managerial and adaptation-based literature (Smit and Pilifosova, 2003) which recognises the importance of enhancing choices and general societal resistance to climate change. Concerning climate risk in water resources planning, soft strategies, which are flexible and reversible, rank high in the adaptation agenda (Hallegatte, 2009). These soft solutions enhance the complete supply/demand integrated system capacity to absorb and to cope with socio-economic shock cascading from climatic disturbance (Nowotny, 1999; Nowotny, 2003). While traditional emphasis has been on the supply and engineering side, there has been a gradual recognition of the need to include cultural and socioeconomic interactions. These interactions can be powerful in driving the demand side and dictating the efficiency of supply options. Given the current level of uncertainties, adaptation strategies have moved toward capacity strengthening rather than optimal decision making (Smit and Pilifosova, 2003; Wilby et al., 2009). This paradigm shift leads to a move from top-down to more adaptive management approaches in the planning process (Ingram et al., 1984; Gleick, 2000; Pahl-Wostl, 2007; Van der Brugge and Van Raak, 2007). Combining both of these stances, Wilby and Dessai () emphasised options improving scientific and climate risk information as well as other water management practices; they further proposed a framework of robust and 'low regret' adaptation by testing both hard engineering solutions and soft solutions against climate impact models, technical feasibility and socio-economic acceptability.

In the context of water resources planning in England and Wales there are several aspects hampering robust planning. As an adaptation decision is shaped by risk information and management responses, the constraints exist at both sides. Regarding the former, risk of source shortages and outages from extreme events and climate change remain highly uncertain; many water companies still have to rely on the observed historic time series rather than climate projections. While climatic uncertainty is significant and largely dominates other factors (Wilby and Harris, 2006), much climate impact information is not provided on a relevant spatial and temporal scale. Furthermore, there is institutional hindrance to incorporate the information in the decision making process (Rayner et al., 2006). Regarding water demand information, there is insufficient water demand data due to the low percentage of households being metered; this leads to coarse resolution in demand projections, and subsequently, the tendency to instead rely on supply management. Moreover, modern water managers are often required to accommodate a wide and often competing range of needs and requirements from stakeholders (Naiman et al., 2002; Poff et al., 2003). Recent implementations of legislation further increase the complexity of the picture. For instance, enhancing environmental standards for water and wastewater can potentially lead to higher carbon emissions, both of which have compliance requirements (Chartered Institution of Water and Environmental Management, 2010). Planned water resource management strategies are often vulnerable to uncertainties in the hydro-climatic cycle and socio-economic changes. While policy guidelines have started to introduce and require the inclusion of uncertainty analysis in the decision making process (Commission, 2000; Water Framework Directive, 2000; Environment Agency, 2008), such implementation is still at an early stage. These contexts call for a change in institutional setting and water management practice that can facilitate adaptation planning regarding climate change impacts. In terms of methodology, these impediments highlight the need of new or combined methodologies that can implement key aspects of the robustness concept and address the multi-faceted, multi-attribute decision making process in selecting robust water resources strategies.

2.3. UNCERTAINTY MANAGEMENT IN WATER RESOURCES PLANNING AND RELATED FIELD

2.3.1. Robustness in adaptation decisions

The **idea** of robustness is not new. Two parallel interpretations of the concept, *robustness to evidence* and *robustness to future change*, have long been used in statistical analysis and managerial science as criteria for sound decisions. In an adaptation context, they can subsequently be translated into two definitions of *adaptation robustness* i) given the current evidence and its likely changes in the future, the option will remain sound and feasible (Fiering, 1976; Kadane, 1984;

Stainforth et al., 2007a; Fox et al., 2009), or ii) the option is kept flexible to enables subsequent switching in the next decision sequence (Rosenhead et al., 1972; Nowotny, 2003; Hirschboeck, 2009; Peel and Blöschl, 2011). Paradoxically, these two criteria propose opposing definitions of a robust decision: the former requires a static option that can withstand uncertainty while the latter keeps changing options to accommodate new conditions.

With time, robustness has constantly been reinvented to incorporate new approaches and thus, frequently merged with the concept of resilience and flexibility (Kundzewicz and Kindler, 1995; Srdjevic et al., 2004). Yet, the dichotomy of the term remains: in robust control theory, a system is robust if system components are unchanged despite model uncertainty (Roseta-Palma and Xepapadeas, 2004; Funke and Paetz, 2011); meanwhile, a social-ecological systems perspective (Anderies et al., 2004; Janssen and Anderies, 2007) emphasises adaptation, in which the system may shifts to a new state of equilibrium after disturbances. With regards to water resource planning, both are useful concepts that reflect different approaches to enhance system resistance to uncertainty. The former appears to be more relevant to the physical side of water resource systems and the latter more aligned with social and ecological responses. For instance, a robust supply system should operate close to its designed performance, but robust demand management policies should promote sustainable water consumption behaviour that is adaptive to different levels of risks.

An application of the robustness concept in a climate change adaptation context highlights the need to expand and enhance the concept, in terms of ensuring the performance of the system against multiple sources of disturbances that may arise from multiple plausible scenarios. Classical decision analysis is largely based on a single probabilistic description of the system while climate sciences and subsequent adaptation plans often need to consider multiple scenarios and ensembles of climate change projections. This wider range of possible futures prompts the scenario-based approach of system and option robustness under multiple plausible futures (Lempert and Collins, 2007).

In practice, robustness has acquired another dimension: economic feasibility and environmental concern. A robust system should not only maintain system performance but should do so within constrained budgets. To take into account the cost factor, the concept of Hashimoto et al. (1982a) introduces the idea of trade-offs between system flexibility and cost. It compares the final cost to the minimum one (only possible if future outcomes are known with absolute certainty at the time of the decision). As the former is often higher than the latter, their differences are considered extra investments to safeguard against uncertainty, or, the cost of flexibility. The system is considered robust if these differences in cost do not exceed a threshold, pre-defined by the decision maker (Jinno, 1995; Kundzewicz and Kindler, 1995; Fowler et al., 2003). Nevertheless, such a comparative approach tends to identify economically acceptable options amongst the sets, all of which might be below the robust threshold, instead of specifying the robust ones (Allam and Abu-Riziaiza, 1988). The approach of Hashimoto et al. (1982a) has hence been expanded and applied in a broader context, including metric combination, multi-criteria decision analysis and scenario-based approaches which consider multiple sources of uncertainty (Fowler et al., 2003; Kjeldsen and Rosbjerg, 2004; Srdjevic et al., 2004; Ajami et al., 2008).

Due to its intricate nature, the multifaceted concept of robustness is not readily quantifiable. Uncertainty can be characterised using numerous indices including crisp sets, single probability functions, and as recently suggested, fuzzy sets (Milly et al., 2008). Robustness criteria mirror such characterisation, and subsequently, can be categorised into statistical robustness (Fiering, 1976), set-based robustness (Rosenhead et al., 1972) and fuzzy robustness (Simonovic and Verma, 2008).

- *The statistical approach* (Fiering, 1976) has a strong link to hypothesis testing and indexes robustness as the possibility of an option being optimal over all other options. Uncertainties considered are statistical sample errors and alternative assumptions in the modelling process such as the number of variables, conditions of constraints and the preferences of decision makers (Fiering, 1976).

- *The crisp set-based approach* (Rosenhead et al., 1972) is the ratio between the number of acceptable choices after and before a decision.

- *The fuzzy set approach (El-Baroudy and Simonovic, 2004)* compares the risk of system failure after and before a decision by examining the overlapping region between the operating system state (e.g. water supplies) and the failure region (or region of high risks) (El-Baroudy and Simonovic, 2004).

2.3.2. Robustness in water resources planning

True to their predecessors, the current interpretations of robustness emphasise the reliability of options and flexibility of the whole system. The following section outlines several approaches that follow this chain of thought.

2.3.2.1.Robust optimisation

This approach arguably dominates the water resource research literature (Ray et al.; Watkins and McKinney, 1995; Goodwin and Wright, 2001; Chung et al., 2009) and combines the approaches of robust statistics, robust control theory, machine learning and robust linear and convex optimisation (Ben-Tal et al., 2009). This set-based and deterministic approach mainly deals with bounded uncertainty, that is, unknown distributions of uncertainty but (assumed to be) known intervals containing the value of interest (Olston and Mackinlay, 2002). Water planning issues are formulated as linear or dynamic programming (LP/DP) optimisation problems under sets of soft and hard constraints. The optimisation model has to satisfy all hard constraints; it can violate soft constraints but would be penalised in the objective function. The solutions selected can either be feasible or optimal, meaning they satisfy the constraints or are the best option within the considered uncertainty domain (Ben-Tal et al., 2009). Robust optimisation explicitly explores the link between the geometry of uncertainty and robust options. In order for the optimisation to be meaningful, the set of feasible solutions is often required to be convex. The characterisation of the uncertainty set U can be further specified to encompass specific uncertainty of perturbation, probabilistic distributions, or relaxed-representation of normal distributions (the ellipsoidal set) of the coefficient sets.

In the context of water resources research, this methodology has been applied on both investment and operational decisions (Ray et al.; Watkins and McKinney, 1995; Watkins Jr, 1997). Robust options contain robust optimal and robust feasible options, selected by specifying constraints such as minimal cost and feasible system reliability (Watkins Jr, 1997). The method offers flexibility in incorporating multi-criteria analysis but can potentially be computationally demanding, due to its highly structured and detailed uncertainty characterisations (Ben-Tal and Nemirovski, 2002). The method is most employed to explore alternative input data and model parameters, uncertainties of which arise from system disturbance and future changes.

2.3.2.2.Real Options Analysis

Real options analysis is a decision technique that focuses explicitly on the sequential nature of decision making. It concerns future options and actively plans for the prospect of new options. While not referring directly to the concept of robustness, the method relies on analysis of flexibility and costs of options, and thus can be seen as a more extended and comprehensive analysis compared to the approach of Hashimoto et al. (1982a). In more recent studies, the approach has been analysed in the context of robust decision analysis (Mahnovski, 2006) and climate risk management (Beare, 2007). The methodology quantifies the cost and added value of flexibility based on net present values (NPVs). Originally coined by Myer (1984), the term “real option” was used in finance theory to include the opportunity cost of options and to value the cost of flexibility (Watkins Jr, 1997; Wang and De Neufville, 2004). In its original form, the method was used to determine whether to invest now or wait. When translated into a water resource-planning context, the method is used to select discrete decisions and the time of action. For instance, Gersonius et al. (2010) employ real option analysis to decide a feasible option for sequential levee enhancement. Assuming that option effectiveness will decline with time, the study investigated various scenarios of option implementation and their associating cost and performance. As a result, the design was kept flexible to allow switching to new options when new information becomes available in the next planning window (**Figure 2.1**).

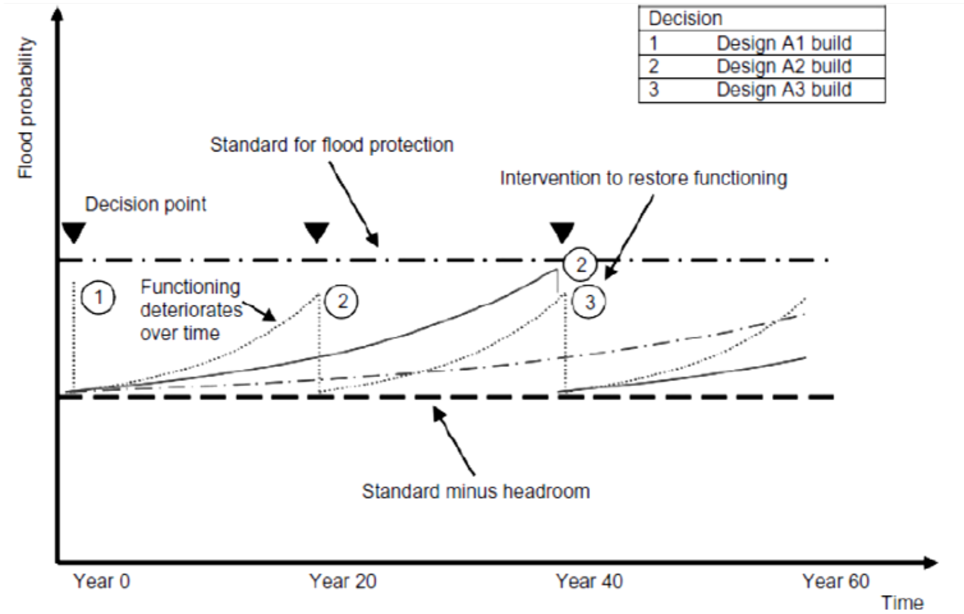


Figure 2.1 Real Option of managed flood probability with time. The effectiveness of each intervention is assumed to deteriorate over time. Design A1, A2 and A3 are three levee options in increasing order of protection. To maintain the flood probability below the threshold for flood protection, there are various possible sequences of implementations, such as gradual enhancement every 20 years or one single implementation with no subsequent adjustment. It was found that for the case of Gersonius et al. (2010), frequent interventions based on newly-updated information appear to be the most effective.While a Real Options approach highlights the flexibility cost of options, it relies on probabilistic approximation of success and failure. The methodology is therefore not readily applicable in the case of deep uncertainty, which by definition offers no reliable probabilistic estimation of risks. The major issues with real option applications in physical systems, as Wang and de Neufviller (2004) have pointed out, mainly concern the lack of clear decision pathways. In its original financial form, options are clearly defined and agreed under contracts; the optimal action is then calculated based on that set of options and their associating probability of profit loss or gain. Meanwhile, real options in the physical systems are highly dynamic and evolve in response to new climate scenarios, demand level or alternative technology. As such, the Real Options approach is a useful methodology to compare the cost of adopting options at different times, if there is sufficient probabilistic information on clearly-defined adaptation pathways, their expected risks and rewards.

2.3.2.3.Info-gap decision theory

The info-gap approach iteratively investigates system performance as system parameters or descriptions deviate from "best estimates", provided by expert judgment or nominal description (Ben-Haim, 2001; Hall, 2003). This reliance on central tendency is in line with certain practice observed in various decision makers (Keeney and Raiffa, 1993), who may be more experienced and ready to start the analysis with central tendency rather than with uncertainty boundaries (Ben-Haim, 2001; Kriegler et al., 2009). The procedure of info-gap starts by determining the system equation, which describes the linkage among major system components. This nominal model $\tilde{r}(x,t,w)$ is an approximation of an actual function of system state r(x,t,w), which remains unknown. An info-gap uncertainty model:

$$\mathcal{U}(\alpha,\check{r}) = \{r(x,t,w): |r(x,t,w) - \tilde{r}(x,t,w)| \leq \alpha\}, \alpha \geq 0$$

Equation **2.1**

is developed as a set of function values around the nominal function with α being the uncertainty parameter. This set is then expanded to explore the ability of management options that govern the system to meet a certain performance criteria as uncertainty grows. In info-gap decision theory, "robustness" (the ability to withstand pernicious change-as defined by the theory) and "opportuness" (the potential for propitious outcomes) are assessed in reference to the potential deviation from the "best estimates". Robustness is displayed and analysed in the form of a robustness function, which indicates "the greatest level of uncertainty at which failure cannot occur" (Ben-Haim, 2006). Opportuneness is displayed and analysed in an opposite function that reveals the lowest level of uncertainty that offers windfall gain. Thus, the robustness and opportunity of each option can be evaluated and ranked based on the preference of decision makers, with the general aims being options with high robustness and low opportuness:

$$\hat{\alpha}(q) = \max\{\alpha: minimal\ requiremnts\ are\ always\ satisfied\}$$

(robustness)

Equation **2.2**

$$\hat{\beta}(q) = \min\{\alpha: sweeping\ success\ is\ possible\}$$

(opportuneness)

Equation **2.3**

As the method uses an uncertainty threshold α to define the domain in which an option is robust, the uncertainty model used in Info-Gap has to be convex, that is, the set of models with a smaller deviation α_1 should be contained within that of deviation α_2 if $\alpha_1<\alpha_2$. While such an assumption might be self-evident in certain systems (Beven, 2008), there is a need to investigate further specific behaviours of water planning systems and options, particularly in the case of interactions within sets of options.

In practice, Hine and Hall (2010) applied Info-gap decision theory on flood mitigation options to consider the timing, value and uncertainty robustness of each option (Figure 2.2). If a preference reversal occurs, decision-makers may trade higher performance for resistance to uncertainty. This graphic portrayal allows decision makers to adjust their performance criteria and in this sense Info-Gap theory dispels two forms of determinacy: a pre-determined probability distribution of potential outcomes and pre-determined performance criteria to be met. In climate change adaptation studies, Info-Gap theory can assess the varying outcomes due to changes of model parameters, structures or future scenarios that deviate from the current state or the “best estimate” scenario of the future (Milly et al., 2008).

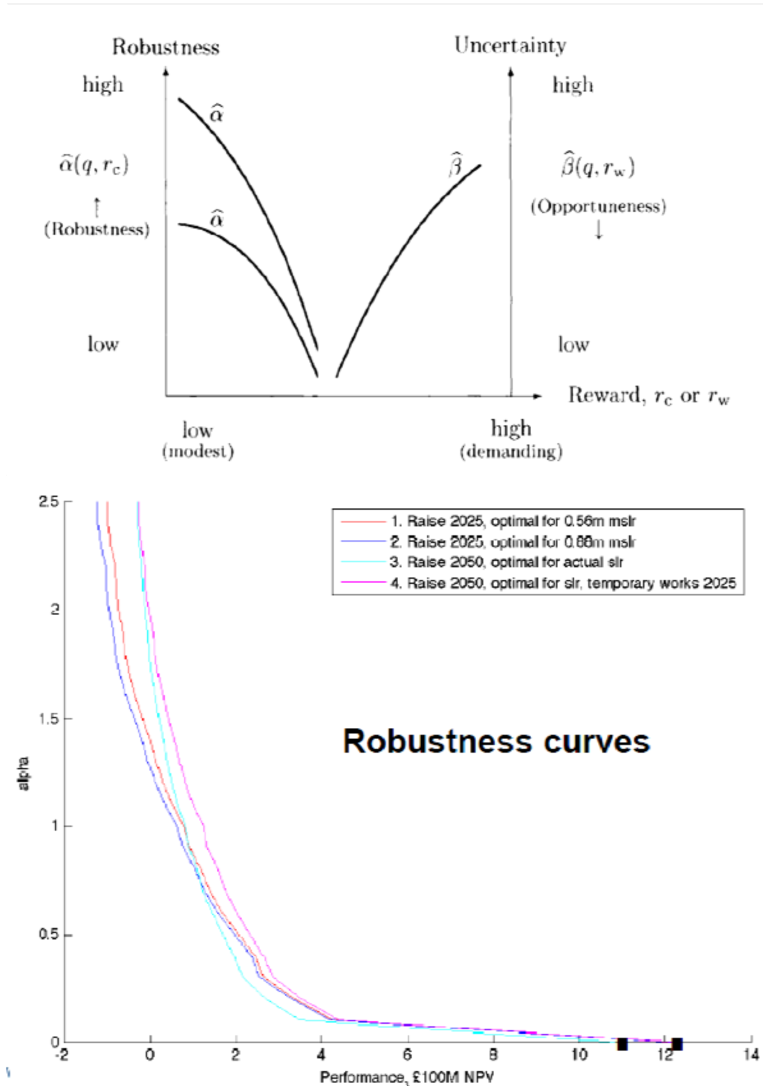


Figure 2.2 Robustness and Opportuneness Curve (Ben-Haim) and robustness curve of a case study of levee raise (Hine and Hall, 2010). The ability of different management options to deliver a desired performance criteria are compared on the same graph with the performance value represented on the x-axis and increasing uncertainty represented on the y-axis. Decision makers can see the amount of uncertainty each management option can accommodate at each incremental measure of performance. In the robustness curves related to the levee raise in Figure 2.2, there is a preference reversal just before the £200M NPV mark. At this point, the ability of option 3 to handle higher uncertainty is surpassed by both options 1 and 2. Beyond this point, options 1 and 2 deliver the same performance as option 3 over higher levels of uncertainty.

2.3.2.4.Robust Decision Making

Robust Decision Making (RDM) uses sets of scenarios to explore plausible futures, emphasise adaptability as a central attribute, and search iteratively for vulnerable conditions (Lempert et al., 2003). Results from robust decision analysis are not fixed: they are kept adaptive to the users and scenarios. This approach does not provide the best rank option and considers that different users might have highly diverse priorities. Robustness is used as the main criterion, along with other sets of flexibility, adaptability and system performance. The approach implements a vulnerability-and-response-option, in contrast to the predict-then-act approach, which is adaptation based on a single projected future (Lempert and Groves, 2010). The common steps in a robust decision making (RDM) framework can be summarised into five main steps (Figure 2.3). In particular, the method formulates the problem and chooses candidate strategies by consulting the relevant stakeholders. It then proceeds to evaluate the identified options and the factors causing vulnerabilities to system performance. Finally, it revisits the initial assumptions and options to explore further the vulnerabilities.

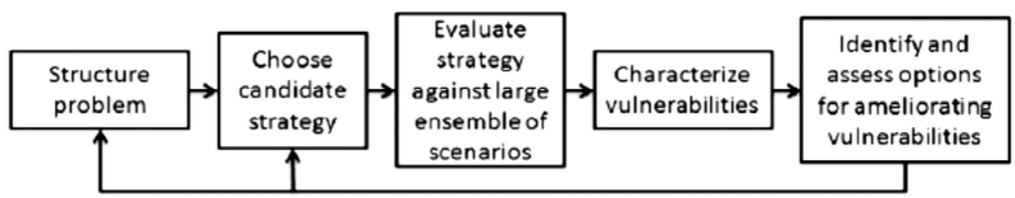


Figure 2.3 Steps in a robust decision making analysis. **Source:** (Lempert and Groves, 2010). The problem is first characterised. Then candidate strategy, which might be single option or a portfolio of options are identified and evaluated under a large ensemble of scenarios. The simulation results are then further evaluated using data mining techniques to identify explanatory factors that lead to system vulnerabilities. RDM can be applied reiteratively to further characterize and identify alternative options or adjusted options, which can mitigate system vulnerabilities.

An example of the method in action is given by Lempert and Groves (2010), in which water planners are interviewed about uncertain key factors in their decision making. The answers are used to construct a model inclusive of the factors, namely climatic changes, future water demand, subsequent changes in imported supplies, groundwater shift, managerial effects and future costs. Decision-makers identified climate change as the key variable for multiple plausible scenarios and consider the candidate strategies on the basis of climate scenarios. Adaptive strategies such as water-use efficiency, recycled-water system, and groundwater policy were then built into the system and activated once supply deficits occur (Figure 2.4). A satisficing criterion was defined as a threshold to identify vulnerable scenarios: if the supply cost is 20% higher than the shortage cost, the uncertain factors are making the system vulnerable and strategies ineffective (Figure 2.5). It then allows Lempert and Groves (2010) to concentrate on these scenarios and further assess the options and their alternatives.

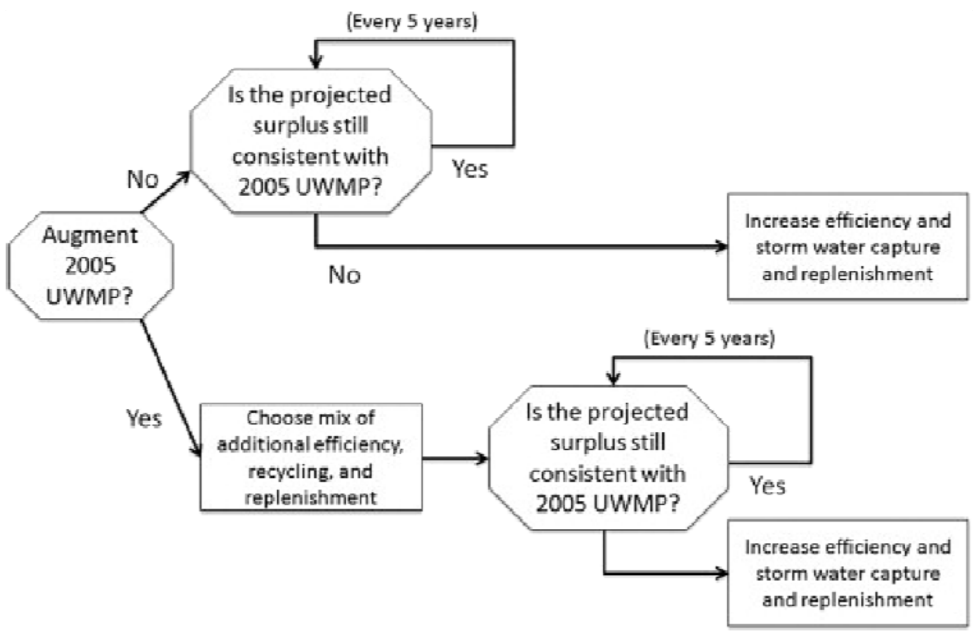


Figure 2.4 Framework of adaptive strategy as implemented iteratively in the model. UWMP stands for Urban Water Management Plan (Lempert and Groves, 2010)

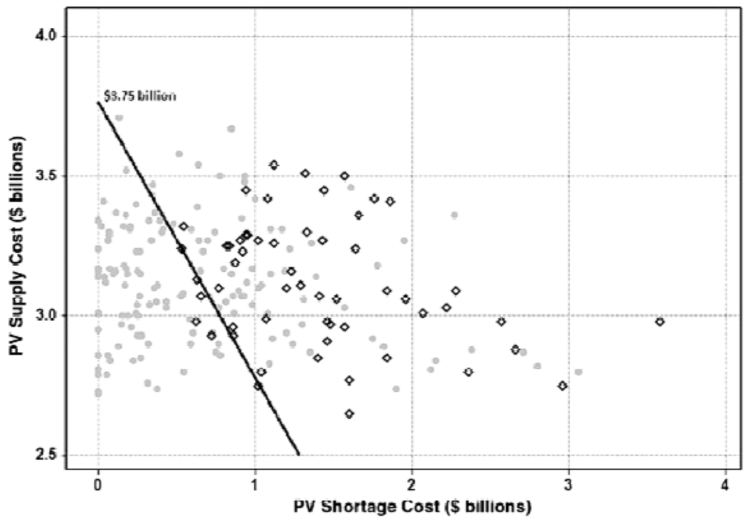


Figure 2.5 Analysis of scenarios, in which the open diamond ones are vulnerable circumstances (Lempert and Groves, 2010)

Robust Decision Making emphasises factors causing system vulnerabilities and options that can reduce such vulnerabilities in the context of deep uncertainty. It stresses the participatory nature of the decision making process by facilitating stakeholders' discussion and visualisation of uncertainties. However, robust decision analysis might be computationally intensive due to its thorough search within the uncertainty space. Lempert et al. (2003) emphasised that the scenarios need to be distinctively different so that the options can be comprehensively analysed and sampled. Similar to other classical approaches, it is also sensitive to the bounded estimation of the sampling space.

2.4. ROBUST DECISION ANALYSIS IN A COMPLEMENTARY FRAMEWORK

2.4.1. Adaptation decision: option robustness and system robustness

As previously discussed, robustness criteria may refer to the selection of a fixed set of options over various possible futures or the ability to switch options should it be beneficial to do so. To some extent, these criteria are tantamount to option robustness and system robustness (Fiering, 1976). Both of these criteria have applicability in water resource planning. As each decision in water resource planning represents an investment, water managers are keen to prove that such investment is worthwhile and the option is robust, particularly when the capital and operation cost are high. Infrastructure options such as reservoir, nevertheless, require a significant amount of time and effort in preparing proposals, impact assessments and preparation. A reservoir's capacity, operation rules and expected operation duration are largely determined by initial infrastructure design; switching away from initial designs at a later stage may become costly. While option robustness ensures that the decision remains correct within a wide range of futures, there is a risk of mal-adaptation due to possible lack of system flexibility. In that context, system robustness becomes relevant. Climate change scenarios introduce a wide and complex range of possible futures for water systems to adapt to, subsequently make adaptive and robust options difficult to achieve. If adaptation methods are flexible and non-capital intensive, future option switching or system enhancement will be more readily implemented.

2.4.2. Comparison of methodologies

The comparison highlights the diversity of uncertainty tackled and robustness criteria in various methodologies. As Table 2.1 depicts, these methods may concern the range of options before and after a decision (fuzzy robustness), trade-offs between performance, flexibility and cost (classical robustness and real options), likelihood of option optimality (statistical robustness, robust optimisation), overall vulnerabilities to changes in system estimates/characterisation (info-gap decision theory), or inherent vulnerable components of the system itself. These methods differ significantly in uncertainty characterisation: the group of Classical Robustness, Statistical Robustness, and Real Options use a single probabilistic description; Fuzzy Robustness use fuzzy logic while Info-gap Decision Theory and RDM are scenario-based.

The main objectives of the methodologies are one of the main foci of this chapter. Classical robustness and statistical robustness both emphasise the low possibility of the conclusion being wrong based on reliable probability estimations of the system and system responses. Meanwhile, fuzzy robustness relaxes the requirement for probability estimations and allows buffer conditions between system failure and non-failure definition. Real options, on the contrary, requires probabilistic outcomes and a clear decision tree of possible option switches. Info-Gap decision theory, largely scenario-based, explores acceptable deviations from the "best-estimate" of system description. It also uses robustness curves to perform sensitivity analysis of a system to each uncertain parameter. RDM is scenario-based and uses multiple plausible futures to explore factors causing system vulnerabilities. Management emphasis and more detailed studies could then be directed towards areas of uncertainty that are the most influential to system performance.

Table 2-1 Comparative analysis of robustness measure and approaches (the classical robustness refers to Hashimoto et al., 1982)

Method	*Uncertainty tackled*	*Robustness Criteria*	*Uncertainty characterisation*
Classical robustness	Model uncertainty	Acceptable trade off between cost and system performance	Single characterization of the system and uncertainty
Statistical robustness	Input data uncertainty	High possibility of the chosen option being optimal	Statistical characterisation of the system and uncertainty
Fuzzy robustness	Uncertainty of acceptable performance	Change in system compatibility before and after the decision	Fuzzy description of uncertainty
Robust Optimisation	Uncertainty of model parameters and input data	Optimal solution, selected by optimisation from the set of all feasible solutions	Can be probabilistic or set-based
Real Option	Uncertainty in time of action and associated cost of flexibility	Low cost of option implementation, switching and adjustment	Option success and failures can be described probabilistically
Info-gap decision theory	The extent to which the system state can deviate and still maintain performance	The management option that satisfies a critical reward at the greatest level of uncertainty	The set of system state clusters around a nominal estimation and form a convex set
Robust Decision Making	Existing vulnerabilities and uncertainty that exacerbates these vulnerabilities	Low-regret strategies that offer acceptable performance amongst all scenarios being considered	The ranges of uncertainty and their interactions can be described in multiple plausible scenarios

To date, uncertainty characterisation has been one of the major factors in selecting a robustness approach. This study proposes that adaptation planning should instead focus on the research question and the level of confidence in data as the starting point of the selection. The argument rests on three main points as follows.

- While the differences among robustness criteria are emphasised in this analysis, they do not exclude complementary usage of these criteria.
- Provided that there is sufficient information that each methodology requires, these robust decision analysis can be simultaneously employed to give a richer picture and understanding of the system in question and their uncertainty components.
- Yet, care should be taken considering whether their assumptions apply. In essence, the sampling domain and types of uncertainty to be dealt with are important.

2.4.3. A framework linking the robustness concepts

The discussion in the previous section has demonstrated that robustness methodologies often exist as a continuum rather than as discrete methods. The uncertainty that they tackle also ranges from total ignorance to knowledge, according to the delineations of uncertainty by Knight (1921) and Beven (2008). These uncertainty domains can be further broken down into set-base knowledge, fuzzy, and probability (Beven, 2008). In Figure 2.6, these degrees of certainty, or better described as level of confidence, are displayed orderly. The figure represents various ways to characterise values of an uncertain variable or model results, all of those reflect the range of uncertainty. Consider the case when X is different system states under climate change impacts.

- If there are multiple equally probable scenarios, the system states under these scenarios can be treated as discrete system states of equal likelihood. They can be further grouped into sets of outcomes, along with their frequency.
- If there is sufficient knowledge to further classify the input scenarios into groups of different likelihoods, these scenarios can then be described under fuzzy sets.

- When there is a high confidence in the information, probabilistic distribution can be used to describe the likelihood, such as, there is a 0.5 chance occurrence of the system state value X

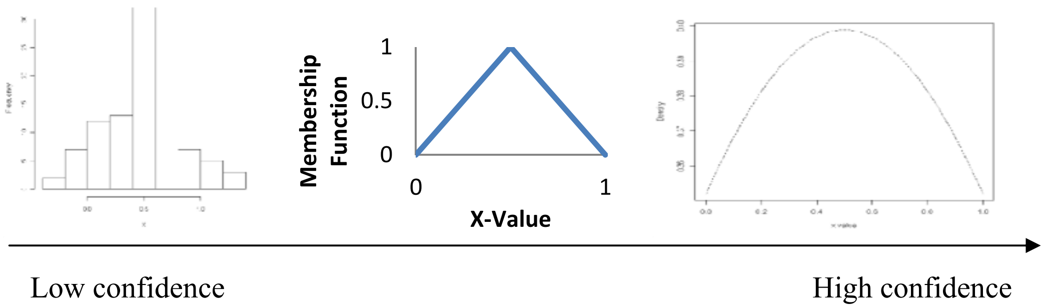


Figure 2.6 Information representation based on level of confidence

As discussed earlier, analysis methodologies vary in terms of uncertainty characterisation and therefore can be mapped along this confidence axis. If the same axis of knowledge confidence is used, the methodologies can be displayed along the axis as depicted in

Figure 2.7.

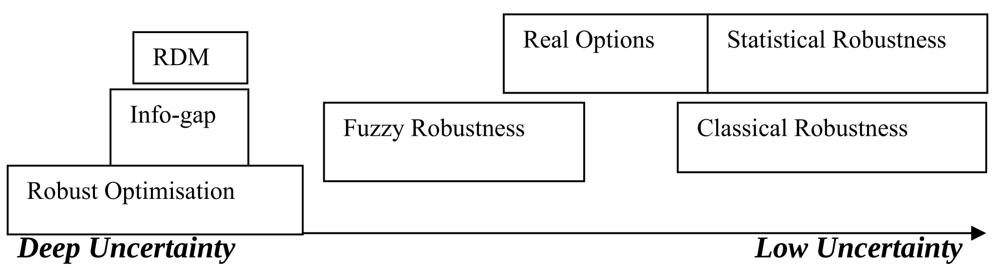


Figure 2.7 Map of methodologies along the uncertainty axis of modelling inputs

This framework proposes that methodologies should not be restricted to their classical confidence domain if the amount of data and the level of confidence change accordingly. Instead, it acknowledges the evolvement of information and knowledge with time and that the decision might be one of multiple iterative decision points. The framework emphasises that the analysis should start with the objectives of robustness and then consider available information (Figure 2.8).

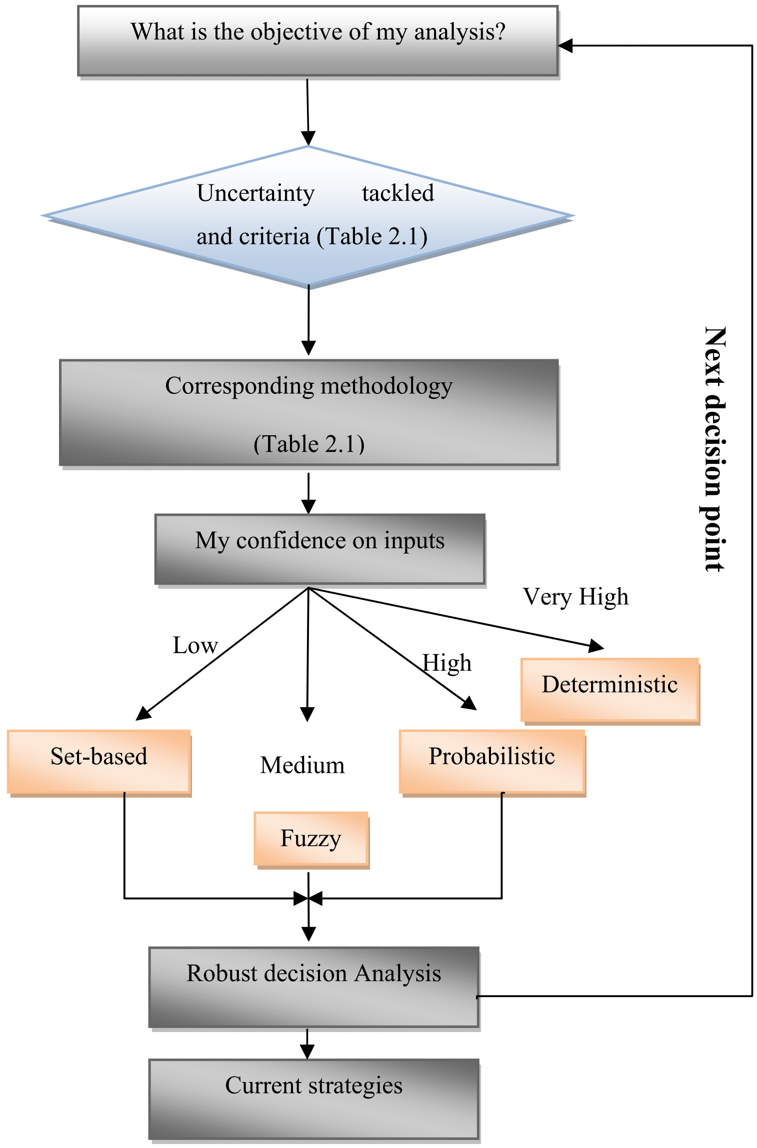


Figure 2.8 Framework for selecting a robust decision method

Furthermore, these switches in uncertainty characterisation can be executed in different decision points. As time proceeds, the domain of knowledge expands while that of uncertainty and ignorance shrinks. These conditions enable method iteration or switching based on the new level of information. For instance, Real Options can first be used as set-based, and subsequently moved towards fuzzy-based and probabilistic as available information allows a more detailed structuring of the outcomes. Similarly, while info-gap, robust optimisation and robust decision making originated as scenario-based approaches, they can be further characterised as fuzzy and probabilistic as newly available information shifts the decision into the domain of less deep uncertainty. As such, at each new decision point, the user can choose to reiterate their previous methodology or adopt a new method to suit their current level of uncertainty. The shift will also reflect their priority of which kind of uncertainty to explore (refer to **Table 2-1**).

2.5.CONCLUSION

This chapter has reviewed various robust decision methodologies and their associated criteria. It demonstrates that each of these methods follows different underlying assumptions and characterizes different uncertainty types and levels. Recent robustness criteria stem from classical groups of statistical-base, rough set-base or fuzzy-based concept. Such diversion in uncertainty descriptions have been captured in **Table 2-1** and Figure 2.4, in which the type of uncertainty characterisation and the evolution of uncertainty level are illustrated. The classical robustness emphasises trade-offs between cost and system performance, and at the same time requires low-regret for the selected decision. Fuzzy robustness is an extension of classical set-based robustness, with the improvements being the usage of likelihood/membership function and a more flexible definition of system failures. Robust optimisation formulates the issue as an optimisation problem under set of hard and soft constraints, the solutions of which are deemed robust feasible and robust optimal solutions. Real option analysis offers a comprehensive analysis of the cost of flexibility, with the limitation being its adherence to probabilistic assumptions. Info-gap Decision Theory focuses on strategies that can achieve the lowest critical performance over the highest level of deviation from the central tendency, or "best-estimate", while RDM targets factors causing vulnerabilities in the system in question. Overall, the differences in assumptions and methods of these approaches do not exclude their complementary deployment. Furthermore, such deployment can be beneficial as it allows deeper understanding of the system and adaptation options.

It is also recognised that robustness can refer to option robustness or system robustness. The former emphasises the superiority of the chosen option across a wide range of scenarios while the latter puts more weight on option switching. It might be possible to have a robust option that does not reduce the possibility of option switching or retrofitting. However, in long-term decisions, system robustness should be prioritised to avoid to mal-adaptation and costly lock-in. It is thus suggested that legislation frameworks and guidelines to the water industry should place more emphasis on system robustness and flexibility. The paper illustrates that water planning should select acceptable options that satisfy the robustness criteria rather than optimal options which might be susceptible to greater uncertainty.

Finally, the chapter presents a decision framework linking robustness methodologies based on their classical definition and uncertainty characterisation. The framework emphasises the utility of methodologies by choosing their objectives as the starting point. It also expands the methodologies into uncertainty domains that are not covered in the original methodology description, thus enhances their usage under other levels of uncertainty. The framework considers decision making as a dynamic process, in which knowledge changes with time and decisions can be revisited in future planning cycles. Overall, the framework helps to clearly define the objective of various robust decision methodologies and structurally tackle uncertainty attached in planning decisions. This framework helps compare and contrast the related methodologies to distinguish existing robustness approaches. This literature review-based framework therefore highlights the principles of robustness that will be the basis for the Methodology chapter, which targets key features of the robustness concept in a multi-criteria robust decision making context.

Chapter 3. METHODOLOGY

This chapter presents the analysis framework used in this study. The framework is a systematic process that links and analyses component uncertainty of climate-related planning decisions. The chapter focuses on the main structure and linking logic amongst the components; Chapters 5, 6, 7 and 8 will further explain specific treatments of each uncertainty component. Section 3.1 first starts with a brief overview of current uncertainty assessment frameworks and their drawbacks. Section 3.2 then proceeds to describe the aims, structure and key points of the framework proposed and used in this study. The chapter concludes with the specific structure and a flow chart of the methodology, which are summarised in Section 3.3 that also serves as a roadmap of subsequent chapters.

3.1.LINKING AND INTEGRATING UNCERTAINTY

3.1.1. 'Top-down' and 'bottom-up' approaches

As Chapter 2 illustrates, methodologies of uncertainty assessment are scattered in various research literatures, from mathematics and operational research to climate impact studies. In climate adaptation policy, frameworks linking these methodologies often either starts from the climate end or the decision end, described as the 'top-down' and 'bottom-up' approaches (Dessai and Hulme, 2004). The 'top-down' approach, as suggested by the Intergovernmental Panel for Climate Change (IPCC), designs adaptation policy to alleviate the vulnerabilities exposed by climate uncertainty (Wilby and Dessai). Meanwhile, the 'bottom-up' approach constructs policy based on the available adaptive capacity and resources- the limiting factors of possible adaptation actions (Smit and Wandel, 2006). These two complementary approaches answer two different questions: the former targets the climate uncertainty envelope while the latter tackles the social adaptive boundary.

Tying together the impact and response end, both of these approaches provide the context and scenarios for adaptation policy analysis. While traditionally, policy analysis has considered multiple scenarios and contexts, the inherent uncertainty in climate change impacts rapidly expands future projections into thousands of scenarios and possibilities. This high level of uncertainty requires a move from scenario-based to risk-based approaches (Jones, 2001; Klinke and Renn, 2002; Keller et al., 2005; Cowell et al., 2006). These risk-based approaches are naturally closer to the 'bottom-up' approach than the 'top-down' one, as vulnerability is context and system-dependent. They focus on impact-scale vulnerabilities and decision-relevant conditions, for instance rainfall and temperature patterns that lead to crop failures, water deficit or ecosystem damages (Risbey, 1998; Liverman, 1999; Lempert and Groves, 2010; Prudhomme et al., 2010; Brown et al., 2011; Brown et al., 2012). These conditions are then used to analyse either key risks projected in the climate model outputs (Brown et al., 2012), or possible enhancements of the area's current coping capacity (Yohe and Tol, 2002; Füssel and Klein, 2006; Thomalla et al., 2006; Füssel, 2007).

The basic structures of selected methodologies are depicted in Figure 3.1. The traditional 'top-down' starts from the global or regional climate models, which output data spatially as square grid boxes of 50x50 to 300x300 km^2. Since this scale is too coarse for most study areas, the data often require further modelling or statistical analysis. These 'downscaled' climate projections then provide input data for the impact models, which generate scenarios for vulnerability analysis. In contrast, the 'bottom-up' Robust Decision Making (RDM) and Decision-Scaling start from the options (Lempert and Groves, 2010).

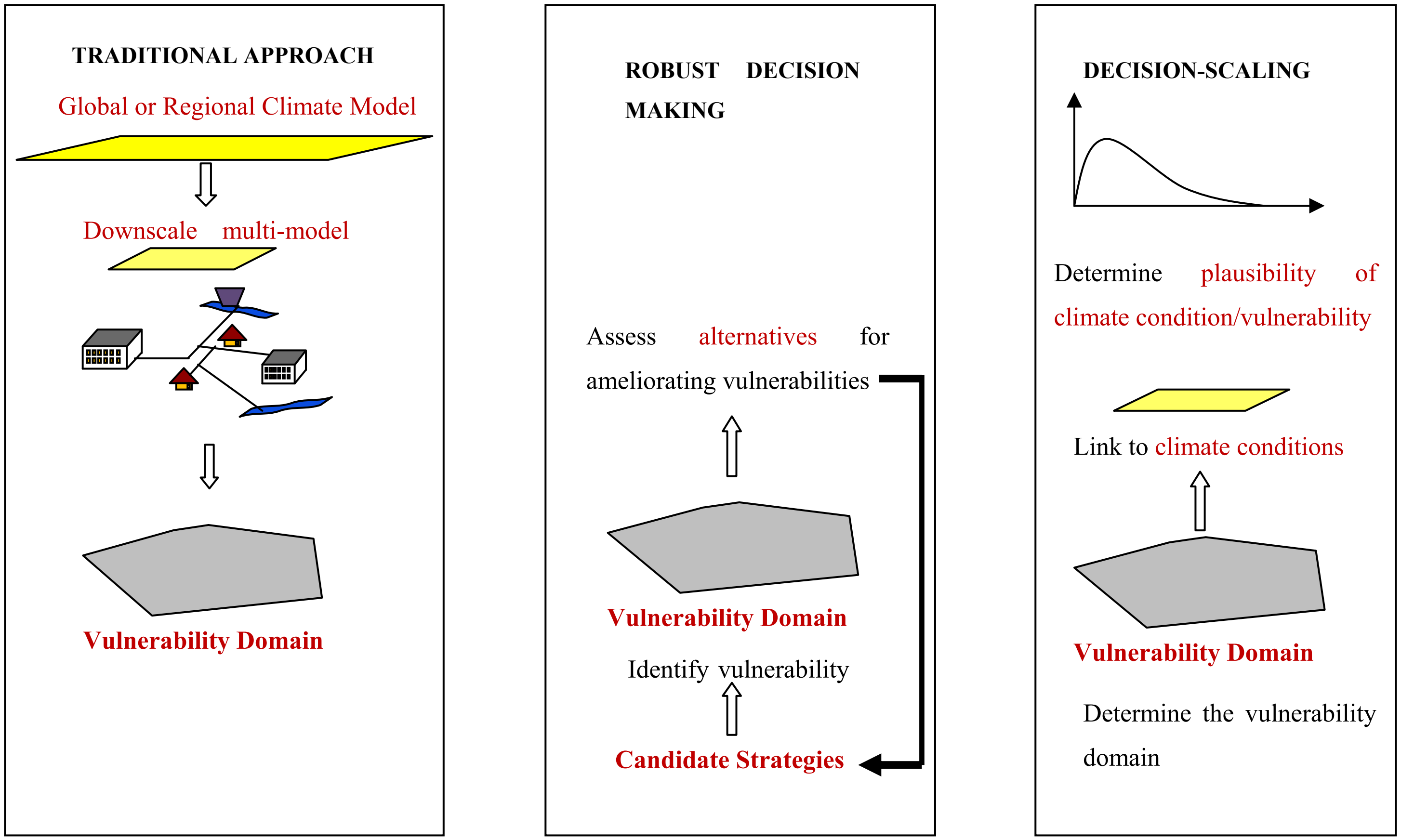


Figure 3.1 Comparative diagrams of traditional 'top-down' and two 'bottom-up' approaches- adapted and combined from Brown et al. (2011) and Lempert and Groves (2010)

In RDM, option performances are iteratively analysed under various scenarios of uncertainty, using user-defined criteria and corresponding thresholds of acceptable performances. The analysts can then change the testing options and repeat the process if various scenarios demonstrate underperformances. Meanwhile, Decision-Scaling constructs a climate response function of vulnerability thresholds, determines the key climate risks in climate model outputs and then uses a decision model to minimise the risks (Brown et al., 2011; Brown et al., 2012).

Besides these decision frameworks, some alternative 'bottom-up' methodologies use the social and ecological resilience lens. In essence, they analyse adaptation as a transition pathway involving state changes and social learning (Pahl-Wostl, 2002; Folke, 2006; Nelson et al., 2007; Pahl-Wostl, 2007). These approaches consider various states of equilibrium that an aftershock society can shift to, as well as major stimuli of these transitions (Geels and Schot, 2007; Vogel et al., 2007; Foxon, 2012). The scope of these approaches often expands to livelihood, governance and policy making as non-climate-based stimuli from the social side (Foxon et al., 2010; Bussey et al., 2012) (Figure 3.2). As such, these approaches play an important role in exploring interactions and responses of social uncertainty that are not explicitly considered in other methodologies.

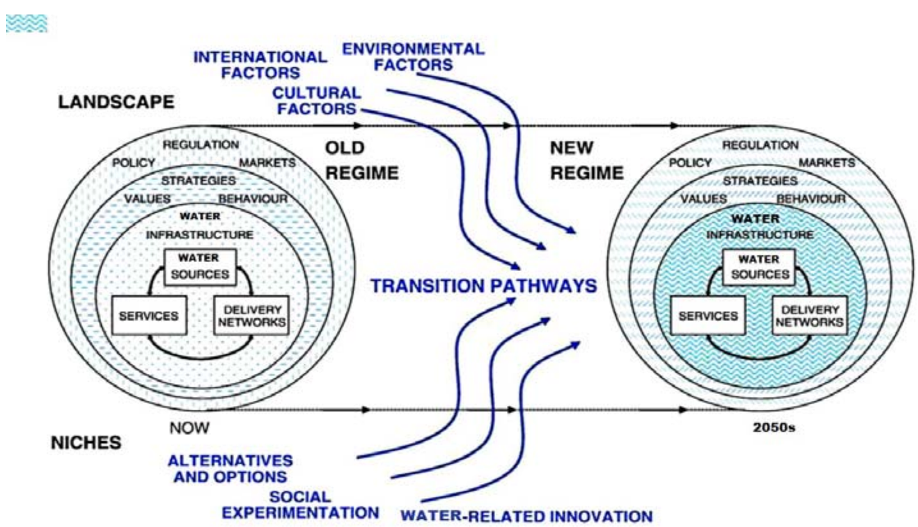


Figure 3.2 Factors influencing water transition pathways. Adapted from Foxon et al. (2010)

3.1.2. Bridging approaches: the challenge

Using only the 'top-down' or 'bottom-up' approach poses problems but bridging these two approaches is challenging. Focus on either the former or the latter can distract or misinform decision makers. 'Top-down' presents an overwhelming level of uncertainty in climate projections, many of which are not decision-relevant or highly uncertain on the impact scale. Meanwhile, 'bottom-up' presents a danger of exclusively relying and focusing on 'known' or experienced risks. There exist very few frameworks that can comprehensively and integrate risk analysis from both ends (Brown et al., 2012) because of four characteristics of the current approaches.

Firstly, uncertainty at either end is essentially different in forms and governing regimes. The top-down uncertainty, coming from physical climate models, is often quantified and shown as projections; meanwhile, adaptation responses are qualitative, fluid and context-dependent. In linking climate and social impacts, qualitative uncertainty is often considered in a separate framework, thus impedes the integrated nature of the uncertainty assessment.

Secondly, both physical and social vulnerability often revolve around the concept of limits and thresholds, a degree of changes that leads to critical transitions or state shifts (Pittock and Jones, 2000; Brown et al., 2011). Yet, crossing a threshold does not automatically prompt adaptation and such thresholds are often hard to determine (Adger et al., 2009). Responses can also vary widely from a behavioural basis (Grothmann and Patt, 2005), as risk tolerance differs from individual to individual due to attitudes, perceptions and decision-making positions (Thompson et al., 1990; Thompson, 2003). Communication of risk is also a key issue: individuals not only react differently to risks but also to different visualisation of the same risk (Gettinger et al., 2012).

Thirdly, adaptation responses exhibit non-linear patterns and may evolve to new information, risks, shocks and surprises. Yet the current approaches largely lack analysis of multi-state shifts and responses to climate change. This missing aspect is important, as adaptation is a process that dynamically balances risks and preparedness. Thresholds and vulnerability of future society are thus different from those of current or historic society. A robust system of today does not necessarily remain so in the future. As such, a robust system has to consider dynamic equilibria, including positive and negative social responses under increased risks such as higher preparedness versus inaction due increased tolerance (Bryan et al., 2009; Foxon et al., 2009; Lindner and Kolström, 2009).

Finally, there is indeed no clear ‘bottom-up’ and ‘top-down’ vulnerability, as uncertainty interacts and grows. The cascade of uncertainty, or the explosion of uncertainty along the layers of analysis (Wilby and Dessai), is likely to expand regardless of the starting point of analysis (Figure 3.3). The process of uncertainty influence is thus not a one-way trickle from the climate end to the decision end or vice versa. Responses to climate and social risks, as such, pose a high degree of uncertainty, as it is highly complex as well as context and path dependent.

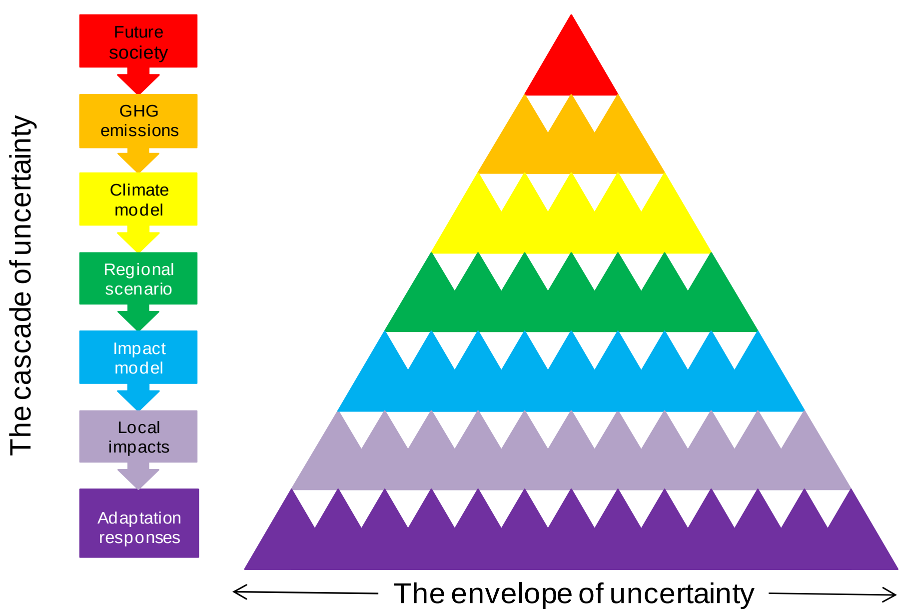


Figure 3.3 The uncertainty cascade (Wilby and Dessai, 2010)

These methodological difficulties translate to the applied side of the decision making process. In the face of uncertainty, responses to risks include delaying action until uncertainty is reduced and mal-adaptation- where actions further weaken the coping capacity (Adger, 2000; Barnett and O'Neill, 2010). Initial adaptive responses might shift to mal-adaptation and disintegrating trust when the climate risks increase (Niemeyer et al., 2005). Yet , water planning in practice still shows a high dependency on historic trends and extreme events (Subak, 2000). Complex decision making tools do not necessarily help alleviate this state: decision makers may respond sceptically or become unsure of how to interpret options and projections (Lempert et al., 2003). An integrated framework of adaptation thus has to efficiently connect uncertainty factors while additionally informing and interacting with the decision makers on key information (Jones, 2001).

To sum up, the current lack of an integrated approach in climate impact research results from inherent differences of uncertainty from the decision and the impact end, problems in defining adaptation thresholds, and the lack of multistate response analysis. Yet, 'bottom-up' and 'top-down' uncertainties are linked and a truly connected approach should include the same key uncertainty regardless of its starting point. These challenges thus call for an integrated methodology that recognises the changing nature of adaptation decision making and with less emphasis on the 'top-down'-'bottom-up' diversion.

3.2.THE ROBUST DECISION ANALYSIS FRAMEWORK

3.2.1. Aims and objectives

In dealing with the challenges mentioned above, this study puts forward a framework that blends relevant uncertainty managements and embraces the changing nature of adaptation decisions. The scope of the framework is to tackle integrated uncertainty in drought planning decisions under a changing climate. This framework assists decision makers in identifying potential pathways that can reduce financial costs and vulnerability to climate risks. The main objectives of the framework is therefore

- To improve computational efficiency of RDM by combining with Robust Optimisation.
- To make decision makers aware of potential trade-offs and uncertainty in adaptation decisions
- To facilitate decision making via multi-criteria risk visualisation, so that decision makers can choose options that match their initial criteria or accept a certain risk level given the uncertainty
- To analyse temporal adaptation pathways that prepare the present water system for climate risks in 2020s, 2030s and 2050s

The uncertainty considered includes climatic, hydrological and water resources uncertainty. Main methodologies in this study include scenario planning, multi-criteria analysis and robust decision making. Three main features characterise the framework. Firstly, the framework integrates various uncertainty factors that are linked by the 'knock-on' effects of climate change impacts. Secondly, it couples multi-criteria analysis and scenario planning to explore the potential impacts of combined uncertainty. The framework combines Robust Optimisation and RDM. It improves the computational effort compared to RDM and provides comparison on sub-optimal options compared to Robust Optimisation. Thirdly, the framework allows decision-makers to change their criteria and criteria priorities in response to updated information or interactions with impact projections. The framework, in support of the study objectives, aims to transform adaptation decision making from being solution and problem-oriented into option-oriented. In doing so, it acknowledges that problem definition and solution selection rest with the decision makers, thus changing in time and from stakeholder to stakeholder. To facilitate changing objectives and perspectives, options are interactively displayed for analysis. Through the framework, decision makers can rethink their adaptation decisions in light of updated information or changes in their adaptation preferences. The framework, however, does not indicate which options the decision maker should choose. Its objective is to help the decision makers analyse and possibly revise choices with an awareness of probable consequences.

3.2.2. Structure

This study proposes a study framework that does not revolve around the ‘top-down’ and ‘bottom-up’ debate. It combines simulation with optimisation to improve the efficiency of option selection. Figure 3.4 presents the steps and characteristics of this framework. As discussed, it is difficult, even unattainable to comprehensively bridge the physical and social uncertainty. The proposed framework instead focuses on adaptation decisions, the outcome of both ‘top-down’ and ‘bottom-up’ vulnerabilities. A robust decision needs to link physical components and possible patterns of social responses to climate change, thus has to compromise the vast uncertainties in climate projections and the specific focus of adaptation at the local scale. In the framework, vulnerabilities are not characterised as black-or-white boundaries that either trigger failures or require adaptation. Rather, it is framed as areas of **unsatisfactory states** or **deep uncertainty**, two conditions that the decision makers may want to avoid. The unsatisfactory state occurs when the system displays characteristics outside of the decision makers’ desired range; meanwhile, deeply uncertain system is a configuration that might work for only a few amongst the wide range of possible scenarios.

More importantly, the framework revolves around the interactive and shifting adaptation preferences, thus makes space for risk negotiation, in which decision makers either seek additional option(s) to achieve their current risk preference, or accept another level of risk. This risk acceptance is not tantamount to inaction or non-adaptation. In many cases, the marginal cost of being insured for a high risk level is much higher than the marginal benefits; in other cases, there is no option that can achieve the desired safety level. By being aware of the risk and taking alternative actions to deal with the risk, decision makers are arguably better informed and more active in the decision-making process. Furthermore, this interactive step enhances decision makers’ involvement in choosing the level of risk and adaptation actions. The framework stresses that decision makers should not feel overwhelmed, outsmarted or deluded by the complex models in the analysis. Making the decision makers central also motivates them to feedback on the model performance or explore ‘top-down’ risk outside of their experience. As the decision makers match model results with their own experience, they can deduce missing factors in the model structure, as well as learning possible inherent risks in their current decision practice. Therefore such practice will lead to the co-development of knowledge between the modellers and the decision makers.

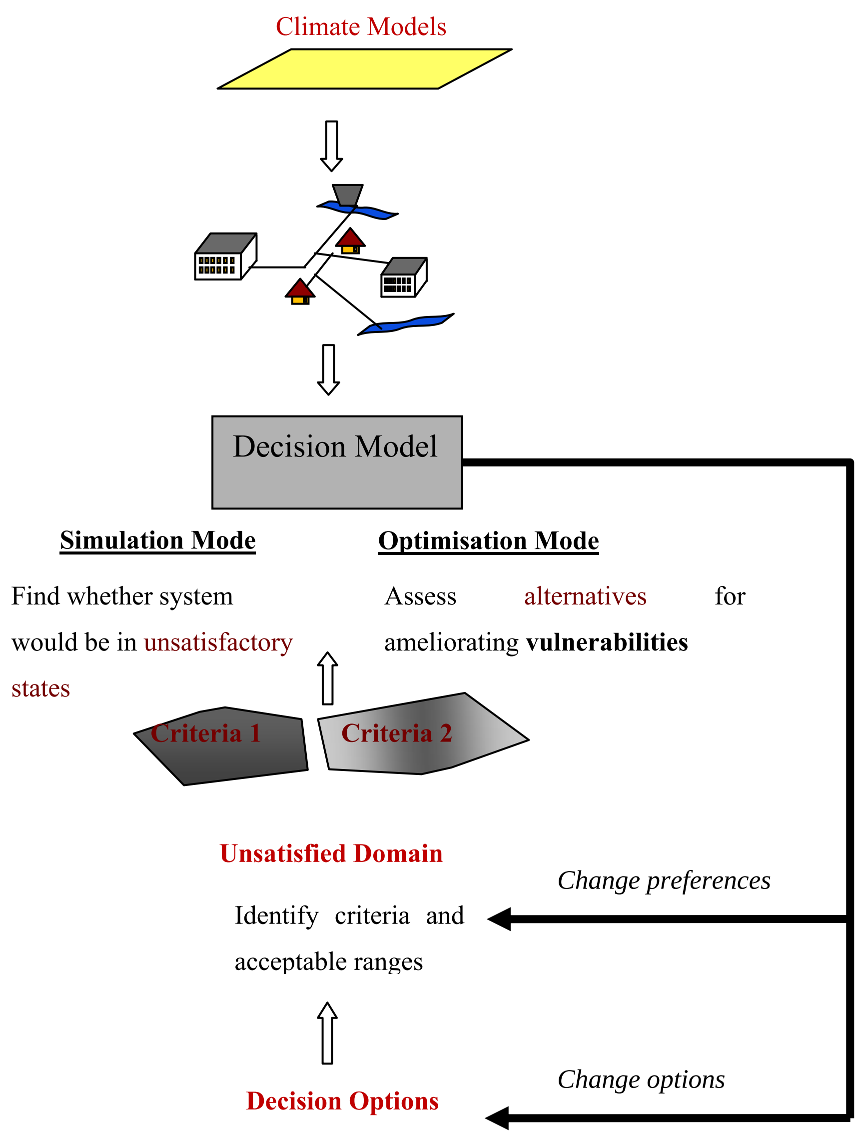


Figure 3.4 Proposed Robust Decision Analysis framework

In order to address these key points, the proposed framework utilises relevant features of decision support frameworks mentioned in Section 3.1. In particular, it inherits the iterative approach of RDM and the efficient and decision-oriented aspects of Decision-Scaling. The framework differs from Robust Decision Making in two aspects:

- **Capacity to change criteria and risk acceptance range:** In RDM, if the decision makers are not satisfied with the option performance, they could further explore other options but could not change their stated decision thresholds. Robust Decision Analysis instead offers the decision makers two choices of changing options or their acceptable risk levels. The decision makers could then investigate the performance of the new options and/or the consequence of changing the acceptable risk levels.
- **The optimisation step which preselects potential options:** RDM presents a framework that engages decision makers to iteratively analyse option by option. Meanwhile, Robust Decision Analysis analyses all available options and their combinations, therefore could present each option performance in reference to other options. This process of identifying potential robust options is useful when the number of options is large and option performance varies greatly under different climate and water demand scenarios.

Furthermore, it has also improved the Decision-Scaling method in two aspects:

- **Dynamic sensitive conditions:** The iterative structure of Robust Decision Analysis allows revisiting and adjusting the thresholds of sensitive conditions (the critical climate conditions influencing planning decisions). Therefore, in contrast to the static sensitive conditions of Decision-Scaling, the sensitive conditions of Robust Decision Analysis can be changed in response to new information from each of the iterations. In essence, the decision makers can assess whether their planning options and response thresholds have sufficiently mitigated the risks, and explore other options or thresholds for planning decisions. Moreover, the discussion regarding threshold and option adjustments can potentially facilitate communication amongst stakeholders and expose their different risk averseness. This participatory agreement on the acceptable risk level is important, as it may lead to further understanding of potential risks each threshold poses for different stakeholders and their acceptability of these risk levels.

- **Analysis of option capacity both under perfect information and deep uncertainty:** Decision-Scaling provides the decision makers with the optimal decisions in different climate conditions. However, it does not identify the overall risks to the system, given the full set of climate projections. Meanwhile, Robust Decision Analysis presents individual and overall option performance under no uncertainty (optimisation mode) and deep uncertainty (simulation mode). The former mode, similar to Decision-Scaling, identifies the optimal decision in each scenario and reduces the computational effort compared to brute force option analysis. The simulation results additionally provide option performance under uncertainty. It therefore compares not only option capacity, but also the level of uncertainty at which an option can operate. Under uncertainty, option performance is determined by various factors, such as proximity to the shortage hotspots and the lead time for an option to take effect. Therefore an optimal option for forecasted droughts might be different from optimal options for sudden drought onset. With Robust Decision Analysis, decision makers can further consider trade-offs between the general capacity of options and their ability to perform under uncertainty.

Compared to both Robust Decision Making and Decision-Scaling, the framework also bears several other minor differences. Firstly, the framework differs in its vulnerability representation. Both RDM and Decision-Scaling use discrete thresholds, which imply abrupt decision switches once the thresholds are crossed. Meanwhile, the framework, as discussed above, considers decisions driven by a continuous range of conditions. It therefore does not automatically assess the appropriateness of options in the adaptation plans; but instead let the decision makers compare option costs and performance and decide on options that match their risk tolerance. Secondly the framework explicitly emphasises the multi-criteria aspect in its analysis and visualisation. While various methodologies rely on the aggregated weighted sum of normalised criteria, the framework utilises an integrated methodology that analyse criteria as independent functions. Finally, the framework employs both simulation and optimisation algorithms: the former assisting vulnerability analysis and the latter optimal decision analysis. Additionally, a combined simulation-optimisation approach can include sub-optimal options for trade-off analysis. For instance, option A is optimal for 40 out of 50 cases and option B 10 out of 50 cases. In the sub-optimal cases, the performance measures of option B are still within the acceptable ranges. If overall option B requires much less capital and labour investment, decision makers can opt for B. The optimisation process can identify A and B when they are optimal for the cases and simulation can calculate performances of other sub-optimal candidates. There possibly exists an option C that is not optimal for any cases but performs adequately at low costs. In this case, decision makers can explicitly switch to the simulation mode. However, computational time, cost and analysis effort grow rapidly when the number of options increases. It is thus preferable that the decision makers carefully assess their criteria and the preferred range. For the example above, option C can still be identified via optimisation if investment cost is included. The approach of coupling simulation-optimisation for this study will be further discussed in Chapter 7.

3.2.3. Data structure

Figure 3.5 presents the specific structure of the framework used in this study. As discussed, the framework retains the interactive element of robust decision making by using inversed optimisation-simulation method (refer to Section 3.2.2 and Figure 3.4). The model first optimises and displays all scenarios and their corresponding optimal options for each scenario. The model then switches to the simulation mode and run the selected options for a subsample or all scenarios. It then outputs the performances of these reference options for those scenarios. The user can then select their preferred options to construct an adaptation pathway. As such, the user can explore whether these preferred options perform acceptably well compared to the optimal option of each scenario. The user can change their acceptable ranges of performance measures by choosing other options that perform less well but still within their risk tolerance.

The framework follows the triggering of climate impacts on the natural system, from changes in rainfall and evapotranspiration to changes in flow regimes and extreme events. It then explores how changing surface water resources will affect possible water management via a water resource model, which generate the water supply and demand balance. Deep uncertainties in climate projections and hydrological model parameterisation are represented in different climatic inputs and hydrological model structures. Furthermore, probable climate effects on demand are also considered, along with demand trends based on socio-economic projections. The process is repeated for each time period of 2020s, 2030s and 2050s (Figure 3.6), so that for each of these time slices, decision makers have several options that they can use to construct alternative adaptation pathways. The study analyses the necessity and performance of options in three time periods (2020s, 2030s, and 2050s). It uses a three-step process of vulnerability identification, robust optimisation to identify potential robust options and cross-checking the results on a larger set of scenarios using the simulation model. In each of these time periods, multi-criteria optimization is used to measure how portfolios of options help keep water deficit, adverse environmental impacts and financial cost at an acceptably low level. These option sets, when being considered along with their capital investment cost, provide useful information on possible adaptation pathways that the decision makers can choose. In essence, the decision makers may first decide on their acceptable level of risk and their financial budget; they then select planning options that satisfy their acceptable risks and costs, and finally construct a pathway of how such options will be implemented in the planning cycles. As such, the framework could assist the decision makers in exploring possible portfolios of options and option performance under uncertainty, and subsequently identifying potential adaptation pathways that suit the users' risk averseness.

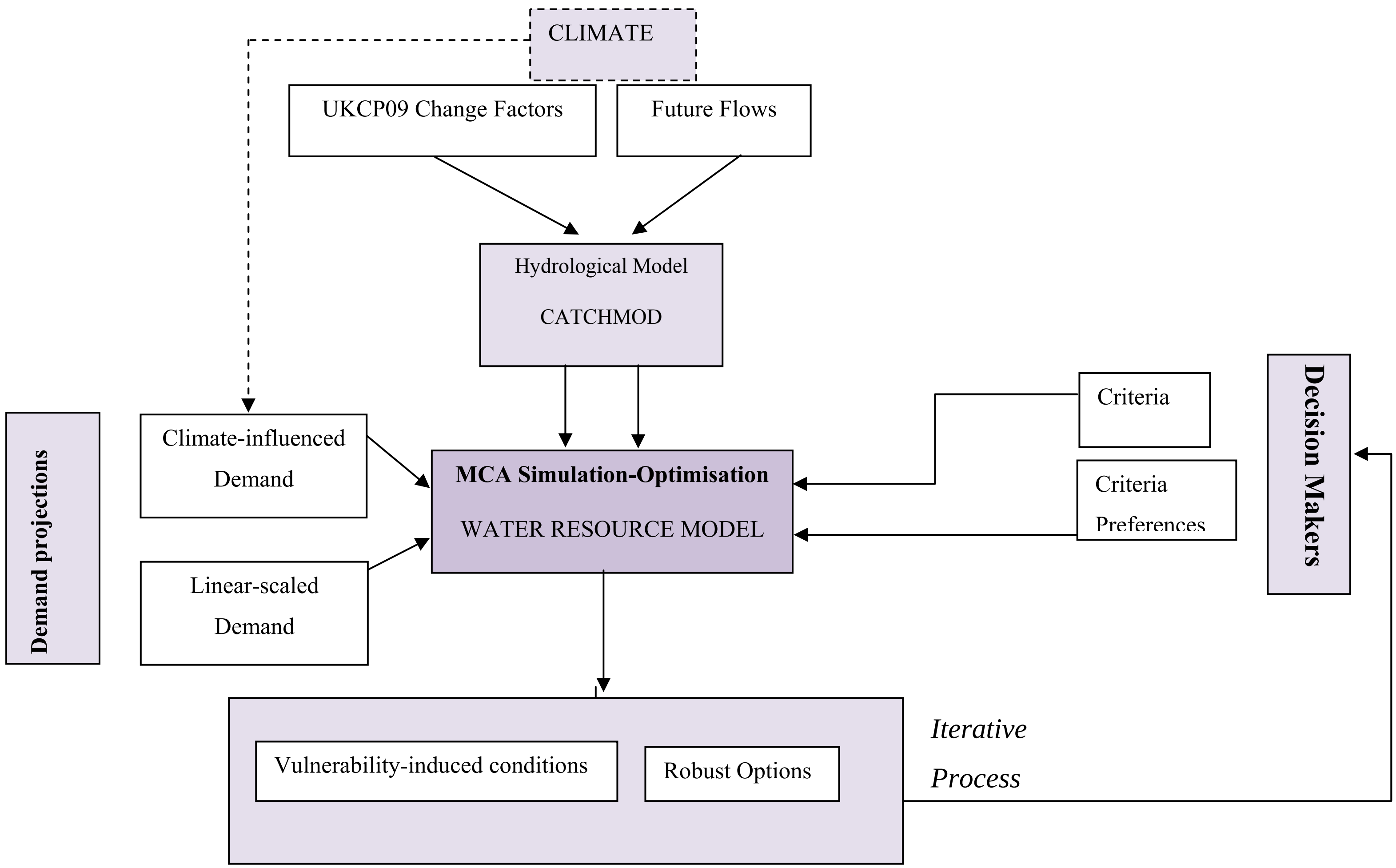


Figure 3.5 Schematic of the framework

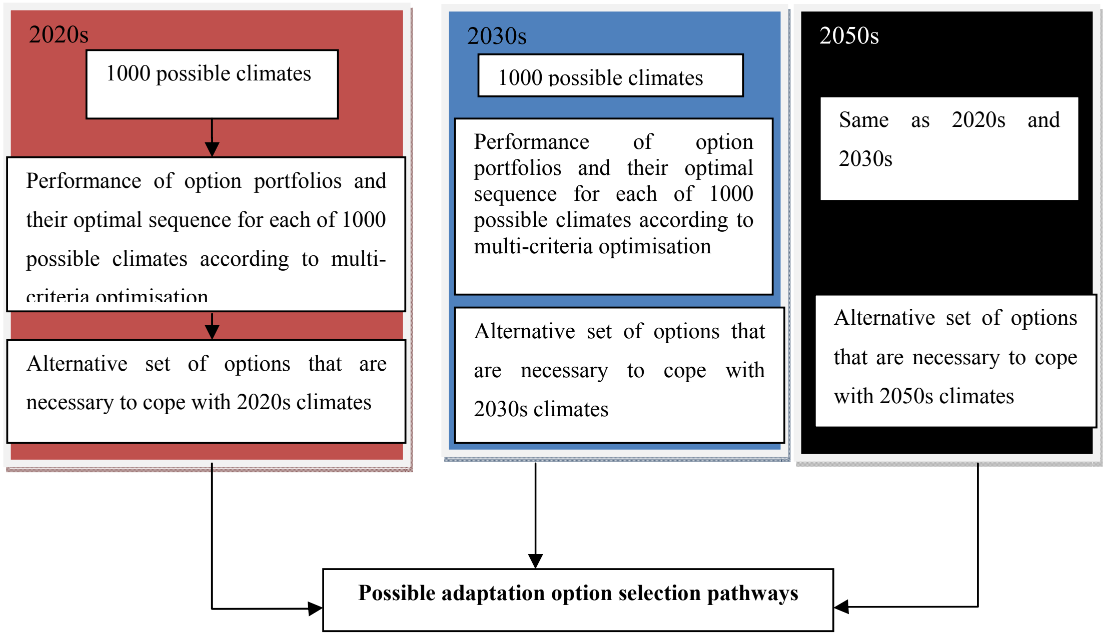


Figure 3.6 Schematic of how the adaptation pathway is constructed based on modelling results

3.3.CONCLUSION

In summary, this chapter proposes and describes an enhanced risk analysis framework that utilises existing decision support tools such as RDM and Decision-Scaling. The approach focuses on the essences of a robust decision in order to link physical and social vulnerabilities. It assesses the shifts in the trade-off preference via iterative analysis steps. A combination of multi-criteria optimisation-simulation and scenario planning is used to explore possible adaptation pathways under deep uncertainty.

The approach is applicable on other systems and types of risks. It is arguably technological-oriented but can implement other soft approaches. While the emphasis of this study is on climate risks, the same framework can be applied to assess any projected changes, such as how water consumption and demographic changes influence water demand. The framework acknowledges the substantial uncertainty from policy drivers. However, it is outside the scope of this study to deal explicitly with this uncertainty factor. The framework does not deal with un-quantified risks, but can potentially use qualitative risks as an extra context for analysing governance and policy influences.

Chapter 4. CASE STUDY DESCRIPTION

This chapter describes the chosen study area and how the methodology in Chapter 3 is applied to the case study. The study area is located in the southeast of England, an area that has been susceptible to the past droughts of 1975-1976, 1995 and the recent 2010-2012 drought (Wigley and Atkinson, 1977; Hopkins, 1978; Marsh and Turton, 1996; Subak, 2000; Marsh et al., 2007; Kendon et al., 2013). Using a spatially coherent stochastic model of monthly rainfall for the southeast, Duan et al. (2012) has shown that some of these past droughts may recur in this region. Another study also demonstrated that the region would require a net water supply increase of 441 Ml/day by 2035, 188 Ml/d of which due to potential climate change impacts (Water Resources in the South East Group, 2010). Medd and Chappells (2007) further asserted that such risk posed a key challenge in building resilience in water management, since the current approach is fragmented and mainly employs engineering measures to ensure supply. To highlight the main challenges in drought planning and the requirements of adaptation decisions, Section 4.1 first describes how water resource management in England and Wales operates; this description helps identify the key decision makers and the major considerations of planning decisions. This decision making process sets the scene for adaptation planning. Based on analyses of the adaptation needs, Section 4.2 and 4.3 then explains how the framework in Chapter 3 will be applied specifically for the study area, with regard to climate uncertainty, hydrological uncertainty, demand uncertainty and water resource uncertainty.

4.1.WATER RESOURCE MANAGEMENT IN ENGLAND AND WALES

4.1.1. A brief description

Water management in England and Wales is a combination of private operation and central regulation. On an operational level, the companies are privately owned and largely responsible for their day-to-day business. On a planning level, water companies are under the auspice of major regulating authorities: the Department for Environment, Food and Rural Affairs (DEFRA), the Water Services Regulation Authority (OFWAT) and the Environment Agency for England and Wales (EA) (Arnell and Charlton, 2009). The EA and OFWAT evaluate the planning of the water companies every five years via two planning reports (Southern Water, 2009b; Southern Water, 2009a; Environment Agency, 2012). The first report is the water resource management plan, which details how the companies will maintain a healthy water supply-demand balance during the next 25 years. The second one, the business plan, outlines how the companies will manage their revenue in the next five years. Additionally the company annually reports its supply and financial performance, along with an environmental impact assessment, to the Water Service Regulation Authority. The business plan, the water resource management plan and monitoring data are assessed in conjunction. In essence, the water resource management plan details the need of infrastructure investments; this need then justifies the changes of water price in the business plan. If the regulating authority does not approve the proposed strategies in the water resource management plan, they can require the company to either revise the plan or adjust the business plan accordingly. These plans also form an important basis to assess the annual monitoring data, as the water companies often use the demand projections in the water management plan as the real demand in water shortage analysis.

Aside from these general planning documents, the companies have to consider other risk-specific planning and relevant authorities. For instance, the Climate Change Act 2008 addresses climate change risks and the adaptation options (Planning & Climate Change Coalition, 2010); the Flood and Water Management Act 2010 requires local authorities to prepare flood risk management strategy and options to alter risks. Drought wise, the company is required to maintain a Drought Contingency Plan, which stipulates drought triggers and actions in the event of droughts. This plan does not have a periodic review; it is amended every time the national policies are revised. The Drought Plan and the Drought Direction 2011 also specifies several types of emergency drought responses such as restrictions on water use and extra supply options (Environment Agency, 2011). Water restrictions at the lowest level are often termed as ‘hosepipe bans’ due to its restriction on 11 hosepipe-related uses.

The Water Resources Act 1991, and later the Environment Act 1995 and the Water Act 2003 set out three additional responses of water companies or Environment Agency in the event of droughts (Department of Environment, 2011).

These three measures are described in Table 4-1 and include drought permit, ordinary drought order and emergency drought order. Drought permits allow water companies to take additional water from specified sources and place restriction on their current sources. Ordinary drought orders let water companies restrict the non-essential use of water while emergency drought orders, also termed ‘standpipes’, further restrict water uses and let water companies provide water to the users via standpipes or water tanks. The water companies use the frequency of these hosepipe bans, such as 1 in 10 or 20 years, as a measure of their ‘level of service’. This level of service is also mentioned in the corresponding water resource management plan, as most water companies aim to maintain a certain level of service.

As such, water management in a water resource zone consists of four main actors, three of them are: the water company that operates in the region, the environmental regulator (the Environment Agency for England and Wales) and an economic regulator (the Water Service Regulation Authority; Oftwat) (Arnell and Delaney, 2006; Sharp, 2006). The planning strategies are also subject to public consultation, which engages the customers, arguably the fourth main actor. Figure 4.1 demonstrates the dynamics of decision making at such scale. The water company interacts with the regulators regarding complying with legislation requirements, preparing their long term plans as well as seeking approvals for drought responses. Additionally neighbouring companies are also an important actor regarding water transfer agreements. Furthermore, the company maintains relations with other groups such as Natural England, river trusts, and other stakeholder groups.

Table 4-1 Descriptions of drought permits and drought orders. **Modified from**: Department of Environment (2011)

	Drought Permit	Ordinary Drought Order	Emergency Drought Order
Legislation	Water Resources Act 1991 Section 79a (as amended by EA 1995)	Water Resources Act 1991 Section 74	Water Resources Act 1991 Section 75
Who can apply?	Water company	Water company or Environment Agency	Water company or Environment Agency
Who authorises them?	Environment Agency	Secretary of State or Ministers	Secretary of State or Ministers
Available actions (subject to conditions or restrictions specified on the permit or order)	**Water Company** To take water from specified sources; To modify or suspend conditions on an abstraction licence held by the water company	**Water Company** Same as drought permits but also: To discharge water to specified places; To modify or suspend discharges or filtering/treating of water held by water company; To modify or suspend restrictions or obligations to taking, discharging, supply or filtering/treating of water held by others (including Environment Agency); To authorise the EA to stop or limit the taking or discharging of water from/to specified sources or places; To prohibit or limit particular uses of water under Drought Direction 2011 (these provisions do not apply for emergency drought orders) **Environment Agency** To take water from specified sources To discharge water to specified places; To stop or limit the taking of water from specified sources; To modify or suspend restrictions or obligations to taking, discharging , supply or filtering/treating of water held by anyone	**Water Company** Same as ordinary drought order Additionally: To prohibit or limit uses specified by water company; To set up and supply water by means of stand pipes or water tanks in a water company area. **Environment Agency** Same as for ordinary drought orders

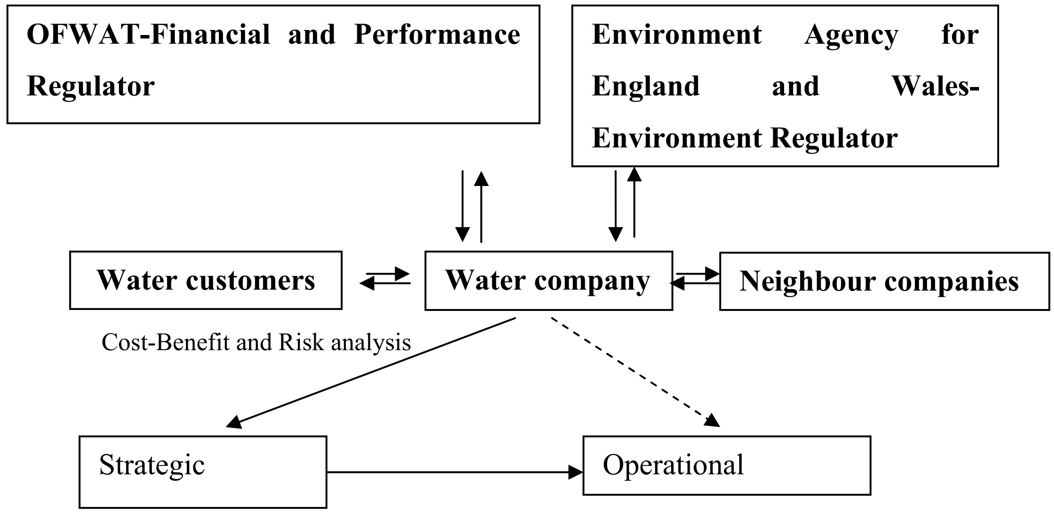


Figure 4.1 Water management framework in England and Wales

4.1.2. Planning decision cycles and decision variables

The structure of water management in England and Wales greatly affects the decision making process of water companies (Cashman and Lewis, 2007). Overall, a water company often focuses on strategic decisions proposed in the water resource management and the business plan. There are two reasons for this focus: firstly, most operational rules are determined at this level; secondly, regulators' approvals or objections at this level may determine the available planning options and the implementation timeline, subsequently affect everyday operations and long-term options. Indeed, the company controls and may vary its operations, but often follows the strategies laid out in the two plans, particularly the short-term business plan.

As water companies are private but heavily regulated firms, their planning decisions have to balance profit making and the quality of their water services (Helm and Rajah, 1994; Ogden and Watson, 1999; Parker, 1999). While this balancing requirement also exists for other industries, for the water industry the requirement is implemented via the close supervision from the regulators (Saal and Parker, 2000). This supervision ensures that the company does not abuse its position to make profit at the expenses of the customers and the environment. Often, a private firm can make money via selling a sufficient number of products and/or setting the price higher than the cost. Since the water companies operate on water, a limited resource, they cannot sell beyond the abstraction capacity. Meanwhile, the water company has a great power in setting the price as the water market is segregated and customers cannot switch to alternative water companies unless they consume more than 5 Ml/day (Cowan, 1997; Southern Water, 2009b). This regulated setting thus can potentially lead to over-exploitation of water resources or high water price. As these possibilities are ruled out under the regulation of the EA and OFWAT, it is then essential that the water companies plan their operation in a cost-efficient manner while satisfying the performance and ecological requirements.

Maintaining these criteria is not easy under the high uncertainty of demand growth and climate change impacts. O'Neill et al. (1998) argued that this higher environmental uncertainty can lead to higher adoption rates of innovations. Marvin et al. (1999) further illustrated such environmental innovations via four pathways of smart metering development that also define the water company and water user relationship. These pathways are termed Monitoring, Gatekeeper, Producer-led and User-led. The first three pathways employs the meters to record consumption and provide the water companies with information for water tariff and supply; meanwhile, the User-led pathway, which Marvin et al. (1999) asserted that was still largely lacking in UK water management, promotes information sharing with water users, so that the users can be more aware of their consumption patterns and efficiency. Nevertheless, demand forecasting is still highly uncertain due to the lack of household demand monitoring (Butler and Memon, 2006; New et al., 2007). As such, management options are still mainly supply augmentation options (Guy, 1996; Medd and Chappells, 2007) and the company is partially facing the classical capacity-expansion under uncertainty problem in operational research (Luss, 1982). In these types of problems, the decision makers have to plan water supply augmentation in a sequence of stages so that water demand can be satisfied with minimum cost (Figure 4.2).

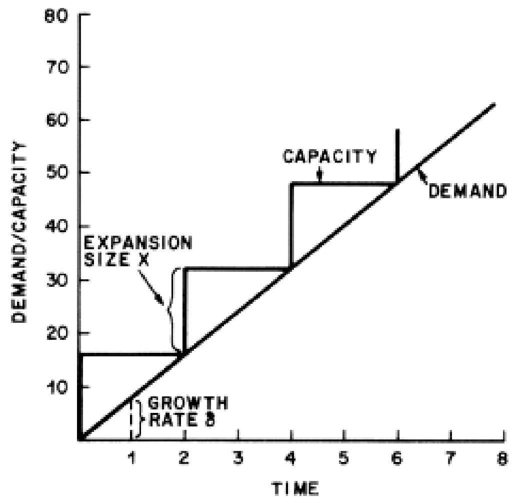


Figure 4.2 Schematic of a capacity-expansion problem. **Source**:Luss (1982)

To include uncertainty and unplanned risks, the water companies are allowed to invest in extra supply capacity. This extra capacity, termed “the headroom”, can account for uncertainty in the supply and demand projections as well as incidences of supply outages (Figure 4.3). It is a formal requirement for water companies to analyse the potential impacts of climate change on demand and supply (Environment Agency, 2012). In particular, the EA allows two approaches to climate change assessment, either by considering climate change uncertainty within the target headroom, or, preferably as a direct assessment on supply sources and demand. In the first approach, the headroom acts as a safety buffer zone where climate change impacts could be accounted for. The second approach represents a more computationally intensive route in which uncertainties are assessed as several components instead of being lumped into a single term of uncertainty. For risk assessment, the companies can further test their water systems against an extreme event, termed ‘the design event’. If the system can withhold against this event, it is assumed to be able to cope with events of equal or smaller magnitude. The return period of the event is also used to describe the system coping capacity to that risk.

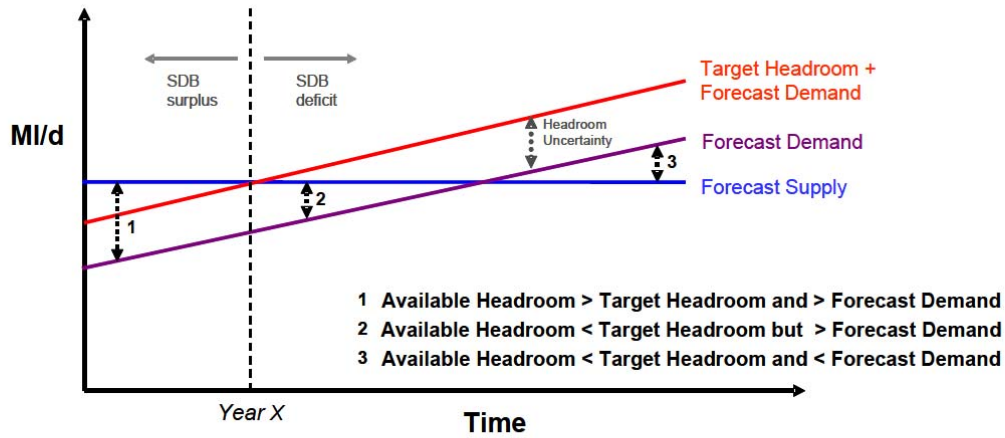


Figure 4.3 The relationship between headroom, demand and supply in the supply demand balance (Environment Agency, 2012). SDB stands for Supply-Demand Balance

Yet, in the capacity expansion problem of the water companies, the planning options expand not only to supply augmentation but also demand reduction and adjustment of current operating rules. Decision variables, the set of strategic decisions that the water company may choose to implement, therefore are divided into three groups

- *Operational* decisions: in which system composition is reassessed. Operational rules such as the minimum environmental flows, the reservoir operational curve, or the drought triggers are adjusted without any further intervention to the water system structure.
- *Supply* management decisions: in which the water company seeks extra supply sources via new constructions of water storage/abstraction infrastructure or other transfer contracts with neighbouring water companies.
- *Demand* management decisions: in which the company uses short and long-term strategies to increase water use efficiency and reduce water consumption.

Table 4-2 demonstrates the sources of uncertainty for headroom calculation from both the supply and demand side. In general the supply factors include source reliability, vulnerability and reduction due to pollution or climate change impacts;

on the demand side, the headroom accounts for errors in demand data and projections, as well as climate change effect on demand.

Table 4-2 Sources of uncertainty for headroom calculation. Source**:** UK Water Industry Research (1998)

Supply-side	Demand-side
Vulnerable surface water licences	Accuracy of demand data
Vulnerable groundwater licences	Accuracy of demand forecasts
Time limited licences	Climate change effect on demand
Reliability of inter-basin imports	
Gradual pollution of source	
Accuracy of supply-side data	
Reliance on single source	
Climate change effect on yield	

4.1.3. Drought planning approaches

The Environment Agency and the water companies follow a 'twin-track approach', which emphasises both supply and demand management (Southern Water, 2009b; Environment Agency, 2012). However, the effectiveness of demand management appears uncertain to many water managers (Subak, 2000). Risk-averse water companies are therefore willing to maintain extra infrastructure to avoid reservoir deficits and subsequent supply failure, since the companies are liable for failing their target level of service. Risk aversion can also be seen in their approach to drought yield estimation, in that they prefer to use the driest scenario from a longer record rather than the required thirty-year historical database (Table 4-3) (Subak, 2000).

Nevertheless, the drought planning trend in England and Wales exhibits a gradual shift from structural measures to non-structural measures. This paradigm shift in drought management can be explained by the changing requirements of drought coping. In the 1970s, droughts were largely due to infrastructure problems (Gibb and Richards, 1978). The 1975-1976 historic drought in the south-east was largely an engineering issue, later solved by inter-area water transfer and additional water resources (Gibb and Richards, 1978). During the 1970s-1980s the supply capacity was further strengthened with leakage reduction and infrastructure enhancement.

Most current water systems have improved their water supply infrastructure and build on multi-source supplies, which helps to alleviate deficits of local sources (Cole et al., 2006). These improvements led to a stronger water system that can cope with the manifestations of past drought patterns. Yet, they are counteracted by three factors: the post-1970s lower public tolerance to water restriction, the growing water demand accompanying rapid population growths and the lack of a national guidance on demand management (Subak, 2000). Therefore, post-1976 droughts such as the 2006 drought have become closely related to the issue of balancing supply, demand and environmental values (Medd and Chappells, 2007). Droughts thus transcend from a purely meteorological and hydrological phenomenon into the social sphere.

Table 4-3 Extracted survey results on managers' perceptions of global warming scenarios by Subak (2000)

	Changes in supply called for because of global warming scenarios?	Comments on Environment Agency scenarios
Bristol	Yes, assume that conditions would be worse than 1933/1934 drought but higher water demand.	Finds the averaging approach reasonable. Believes that the weakest aspect is projecting climate impacts on demand.
Southern	Yes, would move forward in time schemes for new water supply sources	Useful exercise but would rather take the most extreme scenario. Need more sophisticated information on recharge and source yield to estimate potential effects on groundwater.
Severn Trent	Yes, assume that future drought would be more severe than any of the 20th century analogues.	Believe should be using 'the most damaging scenario' rather than the average.
Welsh	No, because expect little variation in supply.	Believe that the scenarios are too aggregated for a region as large as Wales.
North West	No, expect somewhat wetter weather.	Does not like using average year rather than extreme year projections; does not think that using administrative boundaries is suitable.
Northumbrian	No, no significant change in rainfall projected.	No means to project climatic effects on demand.
Yorkshire	No, project slightly wetter conditions.	Not useful to 'average four things that don't have values'. Concerned that factors provided by DETR to estimate uncertainty do not account for differences in the 'persistence' of the factors.

Similar to climate change adaptation, drought coping has also moved into a risk-based approach. Current drought approaches subsequently emphasise the use of contingency plans and insurance policies (Wade et al., 2006). Regarding climate risk, the Environment Agency requires the water companies to consider results from the UK Climate Projections 2009 (UKCP09). Studies based on these projections have already indicated pending risks of higher winter flows and lower summer flows in response to intensified winter rain and less frequent summer storms (Prudhomme et al., 2010; Christierson et al., 2011). Nevertheless, incorporating UKCIP09 results into water resources plans proves to be challenging due to their probabilistic nature and wide uncertainty ranges. There is an urgent need to incorporate climate projections into water supply planning in a practical and timely manner; yet it is equally vital to analyse system robustness given the deep uncertainty of climate projections and other important socio-economic drivers. Amongst these concerns, projected changes in the demand that can be met without violating constraints and causing the system to fail, termed Deployable Outputs (DOs), and headroom assessment constitute prime considerations to water companies (Environment Agency, 2012).

4.2.THE CASE STUDY AREA

4.2.1. Water resources and water management of Sussex

The chosen study area of this study is the Sussex area in southeast England (Figure 4.4). The area is under great pressure to adapt. Population growth and climate change have become two major new challenges for the area and the south-east of England- a region with 15% of its water resource zones seriously water-stressed (Cave, 2009). These pressures may further exacerbate if coupled with a diminishing supply of water, excessive groundwater abstraction and extra demand pressure (Houghton, 2005). Moreover, the region has to rely heavily on groundwater to support the fastest growing population in the UK (Cave, 2009). Climate change, a deep uncertainty in planning, is a big driver for changes in the water supplies (Arnell and Charlton, 2009). Various studies indicate that the UK climate has increased in seasonality over the last 30 years (C.G.Kilsby, 2004; Marsh, 2004; Fowler and Kilsby, 2007) Global climate models (GCMs) project wetter winters and drier summers, thus suggesting more frequent summer droughts to come (Christierson et al., 2011). Using the regional climate model HadRM3, C.G.Kilsby (2004) analyse the IPCC A2 and B2 emission scenarios (UKCIP02 medium-high and medium-low scenarios) for the period of 2070-2100 and find drought duration increasing in eastern and southern regions in both scenarios. More intense drought and an increasing frequency of short-term drought are therefore expected in the future.

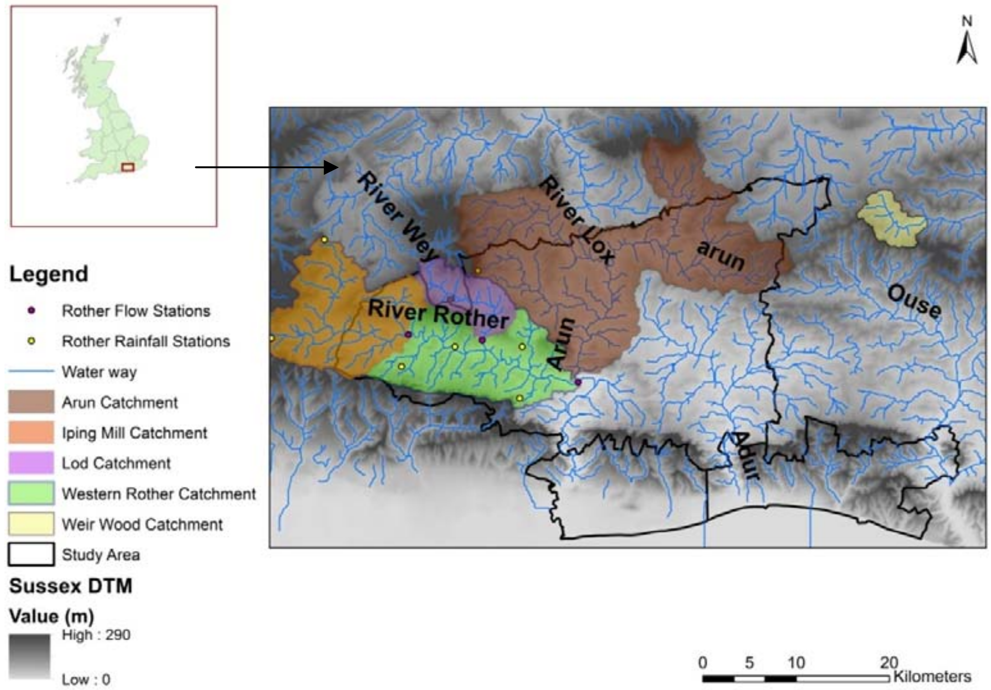


Figure 4.4 Map of the study area. Data courtesy of the Ordinance Survey, Centre for Ecology and Hydrology (CEH) Wallingford and British Geological Survey 2012

The area is divided into three sub-areas: North Sussex, Worthing and Brighton. North Sussex is drained by the tributaries of the Rother (often called the Western Rother to distinguish with the river Rother in East Sussex) the Adur and the Arun. Amongst these rivers, the Rother and the Arun constitute important water resources for North Sussex. Meanwhile, water resources in Worthing and Brighton mainly rely on groundwater. Geologically, the whole study area overlays the Chalk and the Greensand aquifers, which produce moderate to high groundwater yield (Figure 4.5 and Figure 4.6). The water supply of the area relies on the Rother, the Arun and various groundwater boreholes in the Worthing and Brighton area. The water resources of the area are managed by Southern Water Services Ltd., a private company of Greensand Investments Limited. This water company originates from Southern Water Authority, a pre-1989 public water authority, and still retains various management and facilities of its predecessor.

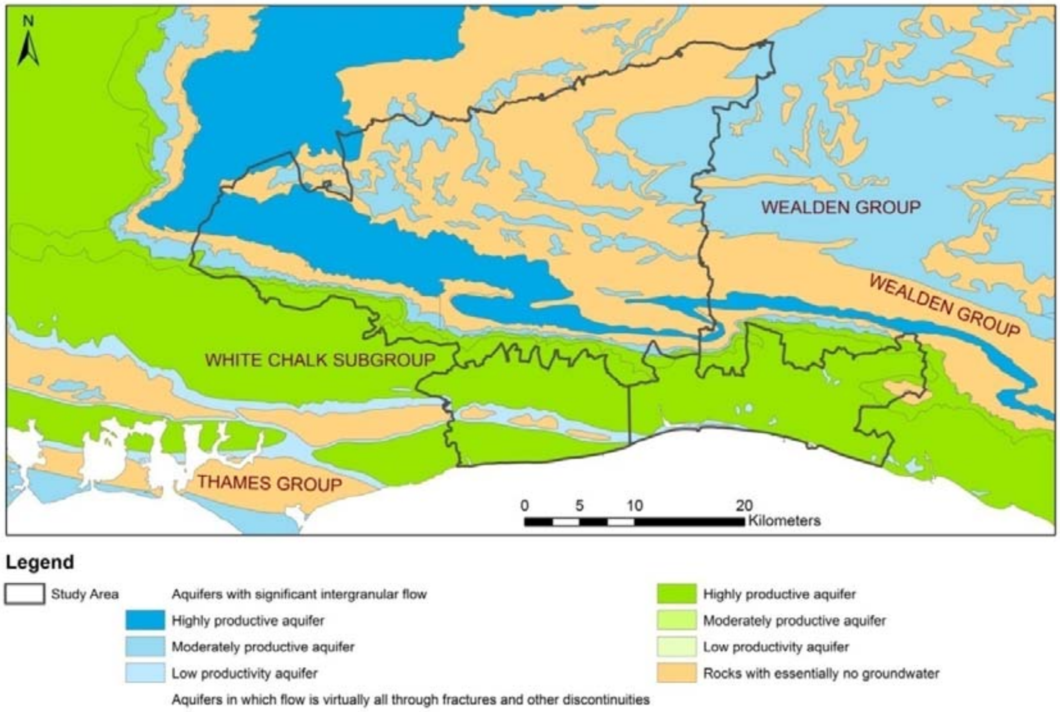


Figure 4.5 Geological map of the study area. Data courtesy of the British Geological Survey 2012

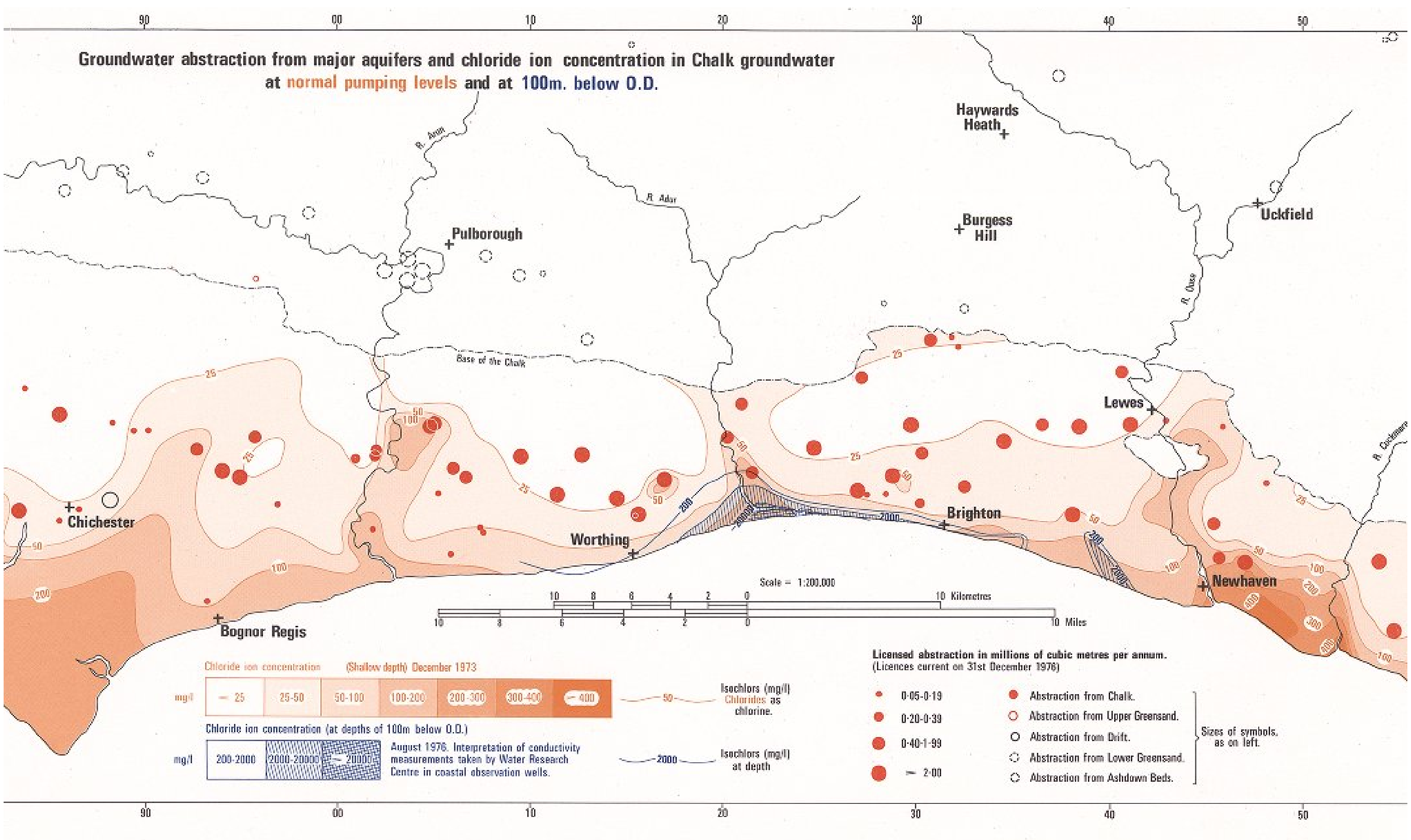


Figure 4.6 Groundwater abstraction map of the study area. **Source:** British Geological Survey

In addition to the surface resources within its administrative boundary, the company also operates the Weir Wood reservoir. Despite its small capacity, this reservoir plays an important role in preserving water for the peak summer period. Southern Water shares the reservoir with South East Water and is obliged to provide 7.5 Ml/day to this neighbouring company. The company also has an ongoing contract with Portsmouth Water, another neighbouring company that supplies up to 15 Ml/day to Southern Water's Sussex North. In terms of groundwater resources, the company is assigned abstraction limits by the Environment Agency.

Similar to other areas in the UK, water consumption and demand in the area have not been monitored until recently. To date, customers have often been charged a fixed price that does not reflect the real water consumption. Water consumption metering started in the 1990s and has reached approximately 50-70% in the study area in 2009 (Southern Water, 2009) (Figure 4.7). Hitherto, this lack of household data is still a big impediment in efficient water planning. To address the issue, the water company has included various demand management options in their water management plan, ranging from water efficiency campaigns to variable tariff.

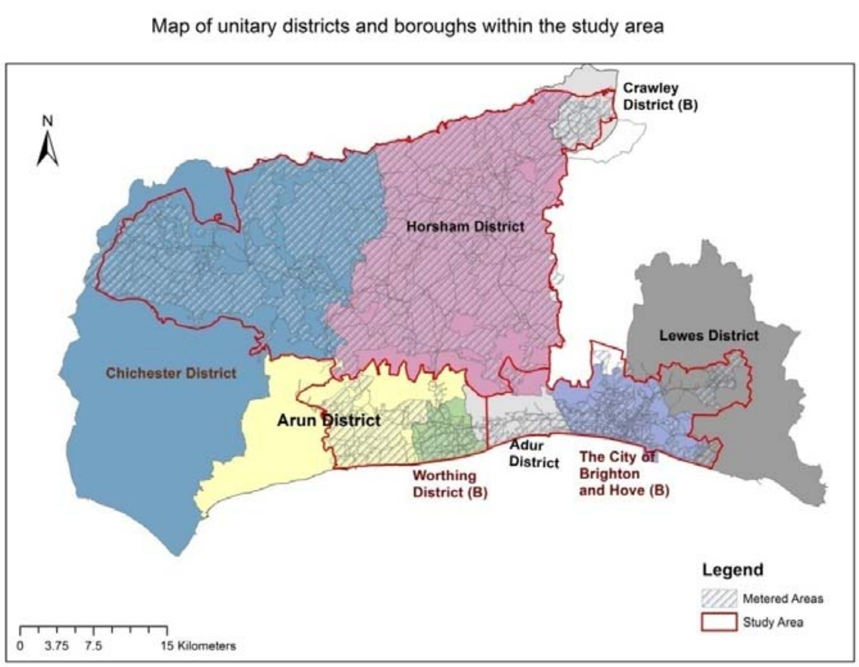


Figure 4.7 Map of metered and un-metered area in the study area

From a planning decision perspective, the company plans its strategies, also viewed as decision variables in decision analysis, via the water resource plans. Its reservoirs operate based on control curves, which dictate when water is stored or released. These control curves are reviewed at the same time as the production plans. For groundwater, as it is difficult to project groundwater sources at the moment, the sustainable available groundwater abstraction is determined as the amount available under the worst drought during 1920 to 1921 in Kent. Operational rules are reviewed as follows:

- Monthly for normal period
- If there are impending droughts: fortnightly review
- Once drought starts: weekly review
- In extreme droughts: daily

For strategic planning, there are the Drought Plan and Water Resource Management Plan. The Water Resource Management Plan makes long-term decisions that maintain the targeted level of service. During the drought period, as described in Section 4.1, response actions could include hosepipe bans, non-essential bans and standpipe.

4.2.2. Main requirements of adaptation: perspectives of the decision makers

Several meetings have been held between Southern Water and the researcher to clarify view points and address adaptation needs. The company recognises droughts as a serious risk in the study area and targets this issue in their adaptation planning. The EA made clear in their Water Resource Guideline (Environment Agency, 2012) that robustness and reliability are key criteria in assessing the water resource systems. The current approach of Southern Water emphasises a resilient and flexible water resource system, based on information and modelling work accumulated from the previous planning cycles. In addressing robustness, the company aims that their options are not only tested against historical droughts but also on synthetic events based on past droughts. In terms of resilience, it tries to maintain the targeted level of service of 1-in-10-year hosepipe ban against the severity of the worst historic drought 1921-1922. The company viewed a resilient option as an option that can accommodate droughts up to the design drought event. In its definitions, there is a significant overlap between the concept of robustness and resilience. Its approach is strongly risk and frequency-based. It specifically analyses the level of service in conjunction with the Deployable Output, the maximum supply that does not damage the water sources and the environment. Via this analysis, the company can assess the maximum sustainable level of Deployable Output that does not affect the sources and worsen the targeted level of service. The company also highlighted the importance of an outage plan, since supply outages in stressed periods might have a significant impact. Compound risks are also a vital factor. For instance, a combination of groundwater droughts and sudden flash floods can severely affect water supply, as the groundwater sources are depleted and the surface water requires substantial turbidity treatment. While maintaining the use of hosepipe bans and the Drought Plan, the company tries to not rely on drought permits, or in other words achieving robustness based on permits, as frequent applications for permits are penalised by the EA. Furthermore, the average time to obtain a drought permit is three months and thus it is highly uncertain whether that permit is still needed once granted.

In terms of demand management, the water company has attempted to apply data mining techniques, such as Artificial Neural Network, to analyse demand patterns. This approach is limited by data availability, since most available demand data is at a macro scale (bulk consumption) and the current available approach is micro-component based. Nevertheless, the company gradually possesses more data on demand patterns and behaviour with roughly ten years of data since metering started in 2000. The current measuring regime, however, reads the meters every six months (and not on the same day for the whole area). Due to this lack of daily household demand data, the company has introduced smart meters which will facilitate more advanced demand modelling. Even so, research based on smart metering data is only feasible after three to four years when sufficient data have been accumulated. To date, most of the work yields limited forecasting power; demand projections are instead based on assumptions on per-capita consumption, the number of households and demographic trends. Similar to supply analysis, the company is using deterministic demand models but aims to shift to stochastic models. The company also remains cautious in demand option analysis, as water efficiency might have been brought down by stealth water efficiency (more efficient white good such as dishwasher and washing machine) and the effect of seasonal tariff is still uncertain.

4.3.APPLICATION OF THE FRAMEWORK

The Sussex area is suitable for a case study because: the decision makers advocate the concept of robustness and resilience; they specify key requirements of their adaptation decision; and relevant data are available for the region. The study thus applies the conceptual framework described in Chapter 3 based on minimising operational cost, supply deficit and environmental flow deficits, the three criteria identified by the decision makers. As the company emphasises the need for robust, resilient and flexible drought planning, the robust decision making framework has been designed to consider the key uncertainties in climate projections and hydrological modelling, while addressing changing water demand. The aim of applying the framework on the case study was to tackle the uncertainty cascade and address the adaptation needs of the decision makers.

This section outlines the data to be used in the framework. More details on the data and how they are used in each analysis component will be provided in the corresponding chapters. The framework, as presented in Chapter 3, addresses climate, hydrological and demand uncertainty and linked by the water resource-decision analysis model. Each component of the whole framework is outlined as follows

4.3.1. Climate uncertainty

The chosen climate projections for the study area are based on the results of the Hadley Centre Regional Climate Model HadRM3 climate model (hereby also termed the RCM in general), a regional climate model of the Hadley Centre produced by the UK Meteorological Office. The chosen emission scenario is the Medium Emission Scenario. The model outputs exist in several forms, such as 10,000 Change Factors of the 2009 UK Climate Projections (UKCP09), the original

11 HadRM3 runs and the Future Flows (FFs) downscaled data from these 11 runs. The UKCP09 10,000 Change Factors are based on a complex methodology that includes the 11 HadRM3 simulations, many simulations of the Hadley Centre GCM, other Global Climate Models (GCMs) and a Bayesian emulator (Murphy *et al.*, 2010). The UKCP09 product adopts a probabilistic approach to represent climate change projections; this approach encapsulates a larger range of results than in previous climate scenarios and is helpful for drought risk identification. Yet, these projections have received criticism on the lack of inter-annual variability and spatial correlation amongst the grids (Chun et al., 2013). By contrast, the 11 runs of the HadRM3 are spatially coherent and include temporal variability but lack the probabilistic ranges of UKCP09. Furthermore, the RCM runs might require bias correction before being used for hydrological models. Based on the original RCM data and historic gridded rainfall data, the Future Flow project has bias-corrected and further downscaled the RCM data. These two sets of outputs thus also have different resolution scales, with the UKCP09 grids being 25 km x 25 km and the Future Flows grids being 1 km x 1 km (Figure 4.8). Hence in this study, these two model outputs are used in parallel to comprehensively capture existing uncertain climate information and address the inter-annual linkage of drought risks.

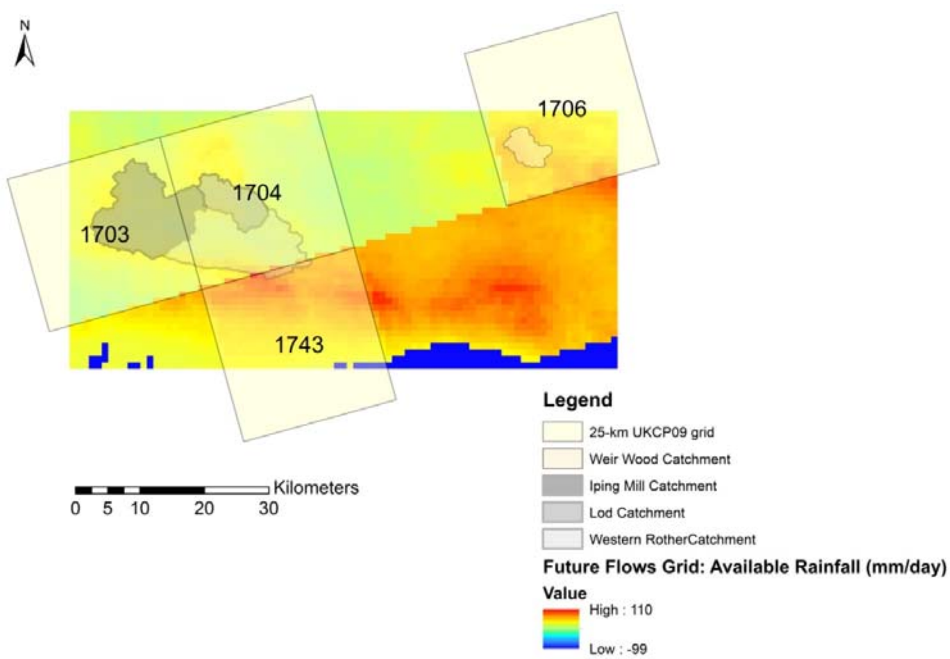


Figure 4.8 **Example of UKCP09 and Future Flow data resolution.** The Weirwood Catchment is located in grid 1706 while River Rother Catchment is spread amongst the grid 1703, 1704 and 1743. The Future Flow data include rainfall and evapotranspiration daily time series from 1949-2099; the UKCP09 sets contain

the mean change factors that can be applied on the historic 1961-1990 baseline time series to present future tri-decadal, such as the 2020s, 2030s and the 2050s. The future flow rainfall presented in this figure is the axfq0 RCM (1 of the 11 runs) run for the 1st November 2099.

4.3.2. Hydrological data and model

The hydrological model used in this study is the Catchment Model (CATCHMOD), a hydrological model used by the Environment Agency and several water companies. The model uses rainfall and evapotranspiration (PET) inputs to simulate surface, subsurface flows and groundwater level. The model represents a catchment as one reservoir, parameters of which present geology, land use and drainage characteristics of the catchment. The water company has been using the model in various submissions of its water management plan. During previous preparation work for the water management plans, the parameters of the model have been calibrated and validated based on the 1990-2005 historic flows of the river Rother and the Weir Wood Reservoir. The calibration period was the 1990-1999 period and the validation period was the 2000-2004 period. In this study, these sets of parameters are used along with recalibration using other periods and calibration criteria. This comparison explores structural uncertainty and parameter uncertainty of the hydrological component.

4.3.3. Demand modelling

In the demand modelling component, the demand projections of Southern Water for 2020s and 2030s are used. For 2050s, the study uses the four EA socio-economic demand scenarios, which project water demand based on different governance and societal structures (Environment Agency, 2008). More details about the demand scenarios will be provided in Chapter 7. Of these scenarios, the Uncontrolled Demand is the most severe scenario that includes substantial population growth and increasing water consumption. In other scenarios, water demand grows or slightly reduces due to innovation in technology and reduced water consumption per capita. The Southern Water and the EA water demand projections were scaled from the 1995 demand profile using a scaling factor, the ratio between the annual average demand of the projected period and the annual average demand of 1995. This scaling process thus preserves the daily pattern of the demand fluctuation and mimics demand changes over the year.

4.3.4. Water resource modelling and option analysis

In the current practice of Southern Water, water resource modelling and option appraisal are separate. The water resource modelling software the company uses, Aquator, is a water resource model that can simulate and optimise the water supply-demand balance at a daily time step. At the current setting, the model is mostly run in the simulation mode, with optimisation being applied to certain bi-directional links of the network. The Sussex Aquator model presents the water system as a network of links and nodes. Groundwater supply is fixed and based on the EA's abstraction licences. Surface water, however, is varied and based on CATCHMOD outputs of Rother and Weir Wood flows. The whole 1888-2005 time series, which include the severe 1921-1922 and 1975-1976 droughts, are used to test the system performance. Meanwhile, option appraisal is analysed in a separate optimisation model that selects options based on their average Deployable Output, investment cost and operational cost.

In this study, the water resource modelling and option appraisal model are combined. This combination integrates the financial investment and performance indicator. Without this integration, option appraisal was based on the expected cost and utility, calculated as

$$C_{option} = f_{option} * E(U) * c_{option}$$

Equation 4-1

With C_{option} being the total cost of the option

f_{option} being the frequency of usages

U being the utility, such as the Deployable Output and $E(U)$ is the expected utility

c_{option} being the cost per unit

By contrast, if the two models are integrated, cost analysis can better reflect option cost and based on the real utility, such that

$$C_{option} = \sum_{0}^{T} U * c_{option}$$

Equation 4-2

With T being the total simulation time

The latter method thus reduces the uncertainty of using the average utility and frequency of usages. Combining the two models will help reduce the analysis effort as climate projections include a large number of cases. The UKCP09 projections consists of 10,000 realisations for each time period; assessing the average frequency and usage for each cases will create 10,000 runs for water resource analysis and 10,000 option appraisals. In comparison, a nested approach readily analyses the options within the runs of water resource analysis and thus eliminate the separate option appraisal runs. Thirdly, this setting can further facilitate changes in criteria preferences of the decision makers, such as using average water deficit instead of the most severe water deficit. When the two models are separated, this change in references would require re-running the water resource model and the option appraisal model. Meanwhile, the integrated model requires only one rerun of the integrated model.

4.3.5. Robust decision analysis

The previous components allow detailed analysis of data uncertainty in climate modelling, parameter uncertainty in hydrological modelling, and model uncertainty in demand projection and water resource modelling. Robust Decision Analysis, in line with the description in Chapter 3, links these components for a comprehensive analysis. In response to Southern Water's point on the outage plan, the framework also includes outage testing, in which supply sources are taken out or reduced to test system resilience.

All the components, as the contributing factors of the water resource assessment, are linked. The uncertainty identified in each component is also cascaded into relevant components, so that their overall contribution can be analysed. The climate uncertainty component is linked with the hydrological component, thus the uncertainty in the hydrological outputs will consists of climate uncertainty and hydrological uncertainty. Likewise, demand projections will include uncertainty from demographic and socio-economic uncertainty. The water resource model subsequently includes uncertainty from all these components; it further adds its own uncertainty in model construction and the decision making process. As such the framework has considered and accounted for certain types of climatic, hydrological, demand and water resource uncertainty (**Figure 4.9**).

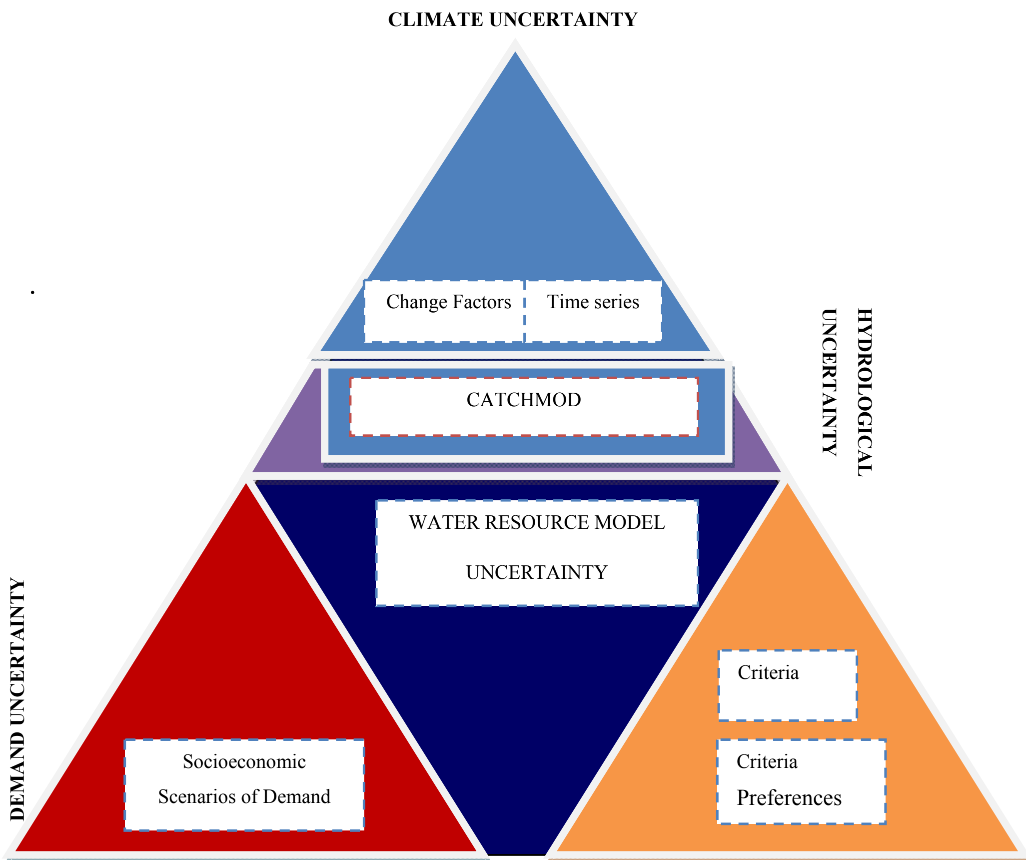


Figure 4.9 Uncertainty factors in the study

4.4.CONCLUSION

Overall, this chapter has described the water resource planning context in the study area, as a region under drought risks in southeast England. The chapter highlighted the four main actors in drought planning at the scale of water resource zones: the water company, the environmental regulator, the economic regulator and the customers. Main challenges in drought planning including robust planning amidst uncertainty, balancing between profit making and environmental services and constructing adaptation pathways given the drought risks. The chapter has also outlined the uncertainty factors to be analysed in the next chapters. In essence, Chapter 5 will focus on climate uncertainty, Chapter 6 on hydrological uncertainty, Chapter 7 on vulnerability of the Sussex water resource system, Chapter 8 on planning options and Chapter 9 on an integrated analysis of robust planning. The chapter also described the study area and its key requirements in adaptation. The area is divided into three water resource zones, all of which are dependent on groundwater. Amongst these three areas, the Sussex North has major surface water sources from the River Rother and the Weirwood Reservoir. The decision makers in the case study have identified the need to adopt robust and resilient water resource planning. Based on the adaptation requirements, the Robust Decision Analysis framework in Chapter 3 has been adapted to consider climate uncertainty, hydrological uncertainty, socio-economic uncertainty and water resource uncertainty.

Chapter 5. CLIMATE UNCERTAINTY

5.1.INTRODUCTION

The south-east of England has been subject to severe droughts in the past and still remains vulnerable in the future. Droughts, as a natural phenomenon, have cascading impacts on the water resources, the ecosystem and the socio-economic system (Dracup et al., 1980; Wilhite and Glantz, 1985; McKee et al., 1993). As a meteorological phenomenon, droughts are signified by precipitation deficiency over an extended period (McMahon and Arenas, 1982). This temporary deficiency may affect water supply for crops and river flows, thus can also manifest as agricultural and hydrological droughts. As droughts do not have a clear onset and ending symptom, it is difficult to identify droughts. Drought types are hence often recognised based on their impacts; classified into meteorological, agricultural and hydrological droughts (Dai, 2011). Traditionally, droughts are assumed to first appear as a meteorological event, when the precipitation does not meet the normal atmospheric balance. These conditions can dry up the soil (soil moisture droughts), lead to plant stress (agricultural droughts) and river flow deficiency (hydrological droughts). The impacts subsequently disrupt the normal operation of the economy and water management, leading to the corresponding drought types. However, with the current changing climate and increased natural climate variability (Arnell, 1999b), drought impacts might occur simultaneously, affecting the most vulnerable system and not in the expected order of meteorological, hydrological and agricultural droughts. As such, drought planning requires information on how the risk arises, what the impending changes are, particularly with regard to changes in climate and local water demand.

Yet, climate change projections are plagued with uncertainty. Uncertainty not only represents our incomplete knowledge of the climate system, but also characterizes the dynamic Earth system. As climate change assessments involve a chain of general circulation models (GCMs), regional climate models (RCMs) to impact models, the uncertainty is set to propagate. The impacts of uncertainty in climate projections can well be traced in drought prospects (Burke and Brown, 2010; Rahiz and New, 2013), subsequent flow projections (Wilby, 2005; Feyen and Dankers, 2009), crop yields (Lobell et al., 2008) and water availability (Fowler et al., 2007; Wade et al., 2013). On a local scale, the added uncertainty may arise from the downscaling process, which adjusts the raw projections to better characterize the local climate (Chen et al., 2011). That wide range of uncertainty further expands when several alternative climate projections are considered. However, many assessments often focus on one climate data source.

The term “climate post-processing” is often used to refer to the process of bias correction or downscaling (Vannitsem, 2011; Imbery et al., 2013). In this study, it is expanded to all general process of converting climate model outputs into products and information of different formats, variables and temporal/spatial scales. To date, studies have demonstrated that post-processing of climate model outputs can adjust the flood risk represented by the final product. For instance, Cloke et al. (2012) have shown that certain post-processing of UKCP09 RCMs can increase uncertainty and further modify the modelled flood risks of the Upper Severn, UK. Kay and Jones (2012) showed relatively consistent median changes in flood frequency amongst the UKCP09 change factors, the Weather Generator, and the UKCP09 RCMs data; nevertheless, due to the data format and the perturbation method, the change factor format leads to less variability than the time series format of the same climate information.

These discrepancies may exist beyond projections of flood risk. As a recurring climate risk, droughts are also subject to the changes indicated in climate projections (Marsh, 2007). While climate information points toward increasing drought risks in the future, they show varying degrees of changes that may be indicative of structural uncertainty and post-processing uncertainty. In particular, the multi-model RCMs of the PRUDENCE project show an increase of short-term summer droughts and lower risks of prolonged severe droughts, albeit with high uncertainty due to the RCMs' poor skills in simulating severe events and other uncertainty cascaded from the driving GCM (Blenkinsop and Fowler, 2007). Using the RCM HadRM3 data from the UK Meteorological Office, Burke and Brown (2010) could recreate observed drought events but found that for the 1959-2002 period the model slightly overestimates drought area while underestimate drought frequency and severity. Meanwhile, the 1960-2080 UKCP09 data project a lowering mean daily river flows for all months in the Medway catchment and with climate signals dominating the hydrological uncertainty (Cloke et al., 2010b). Finally, using the UKCP09 change factors, (Christierson et al., 2011) show a high likelihood of declining summer flows in 70 UK-wide catchments in the 2020s with the main uncertainty coming from the spread in climate projections. These projected reductions and their variation across climate data sources are critical for water resources planning as they may lead to different adaptation plans and implementation schedules. As a potential source of uncertainty, there is a need to examine the post-processing uncertainty in climate products, particularly for those of the same source but having undergone different post-processing methods.

As described in Chapter 1, the focus of this thesis is on water resources drought, defined as a precipitation deficit to the normal functioning of the water system. A comprehensive analysis of water resources drought requires a conjunctive assessment of meteorological, hydrological droughts and the demand pattern. Water resources droughts might originate from insufficient water supply, excessive water demand or a combination of both. Chapter 5 analyses potential drought patterns projected by certain climate models and prepare climate projection data for hydrological and water resource analysis in Chapter 6 and 7. The chapter compares four climate products to investigate the uncertainty of drought projections. Drought severity of each decision scenario, calculated in this chapter, will further be linked to river flow analysis in Chapter 6 and the threshold of decision switching in Chapter 9.

The study is divided into three stages:

i) Analysis of suitable evapotranspiration methodologies for the study

ii) Analysis of historic time series and projections of droughts, based on precipitation

iii) Analysis of historic time series and projections of droughts, based on precipitation and evapotranspiration

The study uses a baseline period of 1961-1990; time periods of interest are the pre-1961 period (1914-1961), the 2020s (2010-2039), the 2030s (2020-2049) and the 2050s (2040-2069).

5.2. METHODOLOGY

5.2.1. Emission scenarios and climate projections

Climate projections are usually the product of climate models, which simulate the Earth's climate system at various horizontal resolutions (Randall et al., 2007). On a global scale, the climate change signals are often assessed using Global Climate/Circulation Models (GCMs). These models divide the Earth into a 100-300 km grid and simulate the climate as the interactions and feedbacks of various atmospheric, hydrospheric, cryospheric and biospheric processes. GCMs can evaluate climatic impacts in response to greenhouse gas emissions; past greenhouse gas emissions are based on historic data, and future emissions are often based on the alternative storylines and scenario families of the Special Report on Emissions Scenarios (SRES) (Nakicenovic et al., 2000). These storylines and scenario families project a probable future world, its economy and global population state; each of these families implies a different level of emission, and ultimately, a different level of climate change. Yet, the GCM results lack the fine resolution needed in various climate impacts and adaptation studies. There are two methods to downscale the GCM results: statistical downscaling, which relates the GCM and the regional climate using historical observations; and dynamical downscaling, which uses Regional Climate Models (RCMs). In the UK, one of the main RCMs is the Hadley Centre's HadRM3 regional climate model, a nested regional climate model using inputs of the Hadley Centre's GCM HadCM3 (for a visual example of the nested RCM approach, see Figure 5.1). Based on the HadRM3 and various international climate models, the UK Climate Projections 2009 produced various groups of climate projections for impact studies.

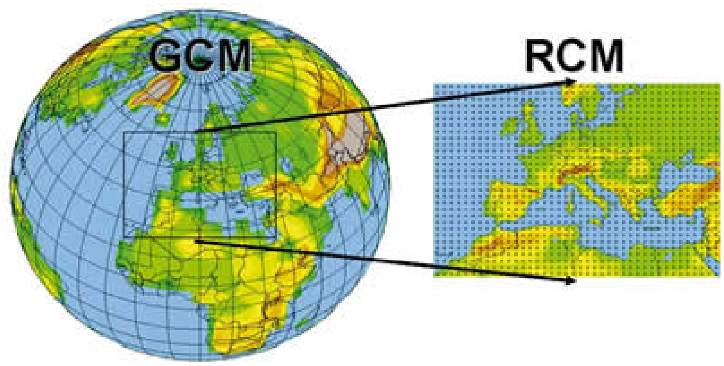


Figure 5.1 The nesting RCM approach, in which a RCM is nested in a GCM to provide climate projections of higher spatial resolution. Source: Giorgi (2008)

This study uses four UK Climate Projections 2009 climate products to analyse the mid-range forcing scenario (SRES A1B). While mainly based on the same 11 runs of HadRM3 Perturbed physics ensembles (PPE), these climate data have further undergone different post-processing to include various uncertainty factors, as described in Table 5-1.

The first product, the HadRM3 Perturbed Physic Ensembles, is a set of transient climate projections for the UK for the period 1950-2100. As part of the UKCP09 project, these runs were used to dynamically downscale a simplified and calibrated version of the GCM HadCM3 that does not include the full ocean processes (HadSM3). The dataset initially contained 17 ensemble members, all of which used parameter settings consistent to those of the driving GCM, but was later reduced to 11 members due to inconsistencies with the driving HadSM3 simulations in the other six. Of the remaining 11, one member represents the standard HadCM3 parameter settings while others explore the range of climate sensitivities and alternative parameter values (Collins et al., 2006). At a finer 25 km resolution than the GCM, the RCM runs use the GCM atmospheric dynamical and physical processes; their boundary conditions come from the corresponding runs amongst 17 HadSM3 members, such as using the HadSM3 simulated time series of temperature and wind. Therefore, they can further include regional physical processes but still largely inherit the uncertainty from their driving GCM. They explore uncertainties in the effects of varying regional physical processes, such as the effects of mountains, coastlines and varying land surface properties.

The second product, the Spatially Coherent Projections (SCP), is close to the 11 RCM runs but has undergone additional post-processing to include a wider set of uncertainties. As the HadRM3-PPE data only contains 11 members, they do not sufficiently sample the uncertainty space that was probabilistically explored in the fourth product: the UKCP09 Change Factors. In essence, the original RCMs did not fully explore the uncertainty in global temperature from emission scenarios, carbon cycle, sulphur cycle and ocean physics. In order to represent the spread that the UKCP09 Change Factors consider, these RCM members were linearly scaled by coefficients. These coefficients are representative of the global temperature changes in the 10,000 Simple Climate Models that produced the UKCP09 dataset. The results were analyzed for coefficient sets that best match UKCP09 data in terms of winter and summer changes in temperature and precipitation for all 25 km grid boxes over the UK for the period 2070–2099. Therefore, the SCPs can be considered modified RCM runs that expand the uncertainty ranges to resemble those of UKCP09, but bear the same limitations of RCMs, such as not including the possibility of a mild increase in summer rainfall in Southern England (Sexton et al., 2010).

The third product, the downscaled RCMs from the Future Flows project has an increased spatial resolution compared to the other products. In particular, it is a downscaled version of the 25-km- gridded RCMs into corresponding time series of 1 km grid boxes. Temporally, the original RCM data were statistically modified to match the observations of the same decades within the 1950-2000 period. Spatially, they are downscaled to reproduce the heterogeneity pattern of precipitation at the 1 km scale. The rainfall downscaling process first used a transfer function to scale the monthly rainfall in each 25-km RCM grid square close to the aggregated rainfall of the corresponding 1 km-gridded observed data. This time series is then further spatially downscaled to reflect the local topographic processes at the 1 km^2 scale (Prudhomme et al., 2012).

Amongst all the products, the fourth product, the UKCP09 product, contains the highest level of post-processing which extends beyond using the RCM-based dynamic downscaling. It also includes structural uncertainty sampled from other GCM through a Bayesian framework. The process starts from running 280 HadSM3 runs perturbing 31 HadCM3 key parameters that control the main processes and the uncertainty space. These runs were then used to train an emulator, a statistical tool that can mimic the effects of parameter variations. To account for structural errors in climate models, single climate projections from 12 other climate models were also checked against HadSM3. From these 10^6 emulator runs, 25,000 runs, later reduced to 10000, were selected based on the likelihood of different model variants and other uncertainty factors. Due to the computational cost, these 10,000 runs were processed in two batches that simulated certain climate variables for each of the 25 km grid boxes. Consequently, while each box possesses 10,000 equi-probable and representative Change Factor sets, they bear no direct relation to the runs in the other grid boxes. In other words, it is unlikely that the changes projected by runs of the same ID in each grid box occur simultaneously over the whole grid.

Table 5-1 Summary of the climate products used in the study

Product name	Acronym	No of members	References	Source	Period	Climate Scenario	Spatial resolution	Temporal resolution	Grid Squares used	Method	Uncertainty sampled
Hadley Centre Regional Climate Model HadRM3 PPE	RCM	11	Murphy et al., 2010	The UK Met Office Hadley Centre	1950-2099	Historical and medium (SRES A1B) emissions scenario	25 km grid	Daily	3	Dynamic downscaling of a GCM with simplified ocean model	Regional atmospheric and land processes; different GCM boundary conditions
Spatially Coherent Projections of UKCP09	SCP	11	Sexton et al., 2010	Similar to UKCP09	Time slices of the 2020s-2080s	4 SRES scenarios	25 km grid	Absolute daily values/ Monthly change factors	3	Linear scaling of the RCM data based on the changes in global temperature from the GCM results	Global temperature changes from emission scenario, carbon cycle, sulphur cycle and ocean physics
Future Flows Project – Statistically Downscaled HadRM3	FF	11	Prudhomme et al., 2012	The Centre for Ecology & Hydrology	1950-2069	Historical and medium (SRESA1B) emissions scenario	1 km grid	Daily	29	Statistically downscaled RCM data based on historic 1km gridded data	Same as RCMs, bias-corrected to a local spatial scale
UK Climate Projections 2009 (Land Projections)	UKCP09	10000	Murphy et al., 2010	The UK Met Office, UK Climate Impacts Program, British Atmospheric Data Centre, University of East Anglia, Newcastle University	Time slices of the 2020s-2080s	4 SRES scenarios	25 km grid	Absolute/ Monthly change factor to be applied on the historic 1961-1990 baseline	1	Bayesian statistical framework drawing from ensembles of Met Office climate models and other GCMs	Structural uncertainty using alternative climate models; emission scenarios; the carbon cycle, sulphur cycle, and ocean physics

Figure 5.2 presents how these four climate products are related. Amongst these products, the 11 runs of HadRM3-PPE are the original and least processed information. The UKCP09 Change Factors capture the widest range of uncertainties but as a result are the most processed product. The format of the products, as used in this study, is also different: the original RCMs and the Future Flows downscaled product are available as absolute daily time series, while the SCP and UKCP09 data are change factors of how monthly values of the variables will shift in the future time slices.

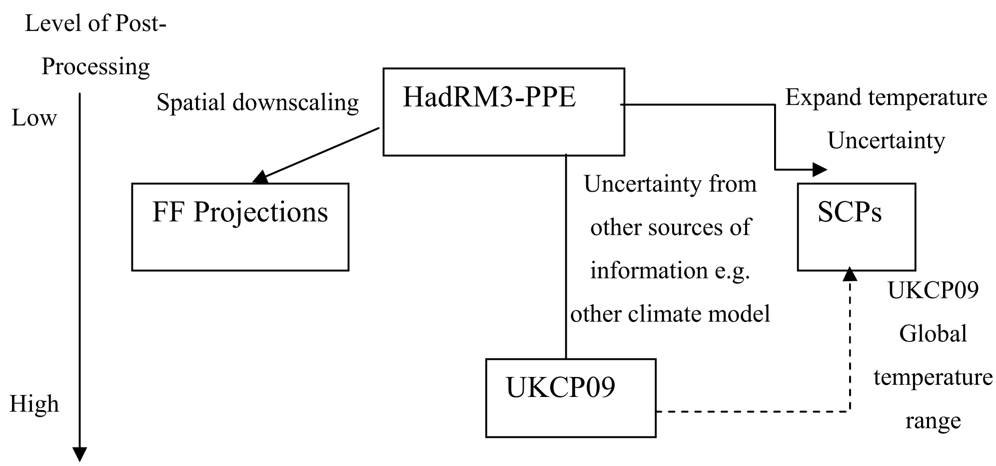


Figure 5.2 Schematic of how the climate products are related

The analysis focuses on four time periods and uses the 1961-1990 period as a baseline for comparison (Figure 5.3). The historic 1914-1960 is termed the pre-1961 period, which is assumed to represent a period of limited climate change signal. The baseline of 1961-1990 follows the Food and Agriculture Organisation convention on climate baseline; this baseline is suitable for The Standardised Precipitation Index (SPI) assessment, which requires an observation record of 30 years or more. Comparisons across the baseline and future periods are made within each climate group, for instance, between the RCM baseline and the RCM projections of each time period. The baseline of the UKCP09 and SCP projections are the historic baseline, as these climate products project future changes as monthly change factors of the baseline time series.

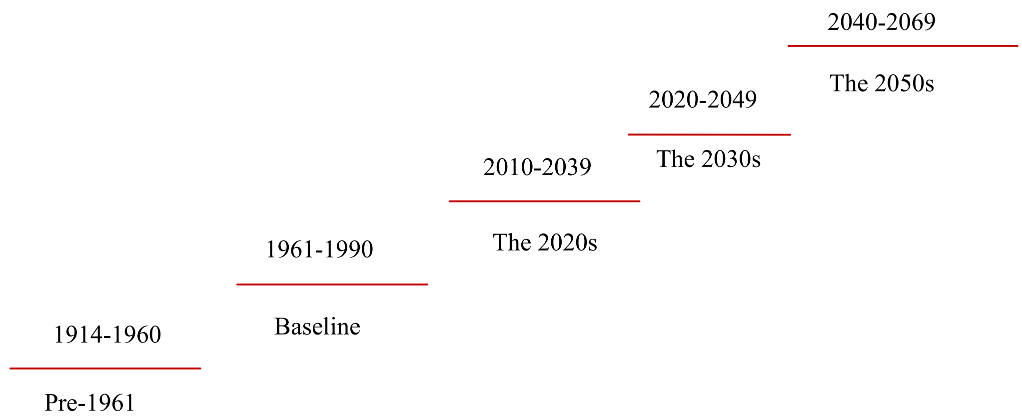


Figure 5.3 Time periods of interest in the study

5.2.2. Drought Indices

5.2.2.1. A brief review of drought indices

While most major drought indices recognise droughts as a prolonged period of abnormal dryness, they use different indicators such as rainfall, river flows and soil moisture deficits (Alley, 1984; Byun and Wilhite, 1999; Keyantash and Dracup, 2002; Morid et al., 2006; Smakhtin and Hughes, 2007). Major drought indices include the Percent of Normal, Palmer Drought Severity Index (Palmer, 1965), Standardised Precipitation Index (McKee et al., 1993; McKee et al., 1995), deciles (Gibbons et al., 2008; Mpelasoka et al., 2008), Standardised Anomaly Index (Katz and Glantz, 1986), the Effective Drought Index (Byun and Wilhite, 1999) and crop moisture index (Palmer, 1968), as summarised by Table 5-2.

These indices indicate droughts as a cumulative deviation from the baseline period; the deviation can be presented as an absolute value, a ratio of the standard deviation or its rank in the total distribution. For instance, Effective Drought Index (EDI) is the needed precipitation to counteract the accumulated deficit since drought onset (Byun and Wilhite, 1996) while Palmer Drought Severity Index (PDSI) is a soil moisture/water balance model that cumulatively measures surface water balance, thus capable of indicating meteorological and hydrological droughts (Palmer, 1965; Alley, 1985; Quiring and Papakryiakou, 2003). Palmer Drought Severity Index

(PDSI), Standardised Precipitation Index (SPI), and Standardised Anomaly Index (SAI) all standardise the baseline, thus facilitate comparison drought incidences amongst different locations and periods. Various comparative studies show that preferences and performance of drought indices vary: PDSI is popular in the US, where it was derived; the decile index performs well for highly variable climate like Australia and South Africa (Mpelasoka et al., 2008); while SPI may be comparable to PDSI and river flows over various sites in the world (Guttman, 1998).

For the UK, Drought Severity Index (DSI) has been frequently used for studies concerning drought spatial pattern (Phillips and McGregor, 1998; Fowler et al., 2003; Rahiz and New, 2013) as well as a drought trigger for drought contingency measures (Prudhomme et al., 2003; Southern Water, 2013). Meanwhile, SPI has been used to assess pan-European drought incidences (Lloyd-Hughes and Saunders, 2002), Spain (Vicente-Serrano et al., 2010) and the UK (Vidal and Wade, 2009). The analyses on UK droughts have revealed that drought occurrences, particularly in the south-east, cluster spatially and temporally. As such, they pose great challenges to water resource management that has to consider the risk of regional water supply deficit spanning a prolonged period. Studies on future drought projections based on both SPI and DSI (Blenkinsop and Fowler, 2007; Vidal and Wade, 2009) generally indicate GCM as a major source of uncertainty, and that drought risk will gradually increase particularly with regards to short and intense droughts of three to six months.

As the next chapter will analyse hydrological droughts via a hydrological model, this study focuses on meteorological drought analysis. The Standardised Precipitation Index and the Standardised Precipitation-Evapotranspiration Index are chosen as drought indices due to their robust capacity to identify droughts, their simple data requirement and their ability to indicate droughts at various timescales. The analysis will also link to hydrological and water management droughts assessed in Chapter 6 to Chapter 9.

Table 5-2 Characteristics of some drought indices. **Source:** Byun and Wilhite (1999)

Name	Factors used	Timescale	Main concept	Source, year created
PDSI	*r*, *t*, et, sm, rf	m (2w)	Based on moisture input, output, and storage. Simplified soil moisture budget.	Palmer (1965)
RAI	*r*	m, yr	Compared *r* to arbitrary values of +3 and −3, which are assigned to the mean of 10 extreme + and − anomalies of *r*.	Rooy (1965)
Deciles	*r*	m	Dividing the distribution of the occurrences over a long-term *r* record into sections, each represents 10%.	Gibbs and Maher (1967)
CMI	*r*, *t*	w	Like the PDSI, except considering available moisture in top 5 ft of soil profile.	Palmer (1968)
BMDI	*r*	m, yr	Percent departure of *r* from the long-term mean.	Bhalme and Mooley (1980)
SWSI	P, sn	m	Weighted average of standardized anomalies of the main elements of the water budget.	Shafter and Dezman (1982)
SMDI	sm	yr	Summation of daily sm for a year.	Hollinger et al. (1993)
CSDI	et	s	Summation of the calculated et divided into possible et during the growth of specific crops.	Meyer et al. (1993)
SPI	*r*	3 m, 6 m, 12 m, 24 m, 48 m	Standardized anomaly for multiple timescales after mapping probability of exceedance from a skewed distribution	McKee et al. (1993)
RI	*r*	yr, c	Patterns and abnormalities of *r* on a continental scale.	Gommes and Petrassi (1994)
RDI	*r*, *t*, sn, st, rs	m	Supply element–demand element.	Weghorst (1996)

Abbreviations: P—factors used in PDSI, *r*—precipitation, et—evapotranspiration, *t*—temperature, sm—soil moisture, rf—runoff, sn—snowpack, st—streamflow, rs—reservoir storage, w—week, m—month, s—season, yr—year, c—century, 3 m—3 months.

5.2.2.2.The Standardised Precipitation Index

The Standardised Precipitation Index McKee et al. (1993) presents droughts as precipitation deficit over multiple timescales. SPI is simple to compute, able to represent different types of droughts, and works consistently across climatic regions (Hayes et al., 1999). The calculation procedure of SPI at scale *i* includes the following steps

i) Prepare a dataset of monthly precipitation

ii) Calculate the moving average of the previous *i* months

iii) For each month, fit the data to a suitable probability density function such as the Gamma distribution, the Gumbel distribution and the Pearson III distribution (there are 12 distributions representative of the baseline distribution of each month)

iv) Transform the probability density function into the standardised normal (Gaussian) distribution

v) Calculate the precipitation deviation away from the baseline distribution

SPI values can be further classified into events, such as floods and droughts. Droughts are identified in months of negative SPI values (Table 5-3). By definition, the proportion of droughts in each category is fixed: regardless of the baseline, the mild droughts, moderate droughts and severe droughts always have an event probability of 34.1%, 9.2% and 4.4%. Subsequently, these events have a return period of 1 in 3 years, 1 in 10 years and 1 in 20 years.

Table 5-3 Classification of droughts according to SPI values. Source: McKee et al. (1993)

SPI Values	Drought Category	Probabilities of occurrence	Approximated Return Period
0.00 to -0.99	Mild drought	34.1%	1 in 3 years
-1.00 to -1.49	Moderate drought	9.2%	1 in 10 years
-1.50 to -1.99	Severe drought	4.4%	1 in 20 years
≤ -2.00	Extreme drought	2.3%	1 in 50 years

As the SPI uses only precipitation, it is based on the assumption that precipitation variability is the main determinant of drought prospects; the effects of other variables such as temperature and potential evapotranspiration (PET) are negligible.

5.2.2.3.The Standardised Precipitation Evapotranspiration Index

The Standardised Precipitation Evapotranspiration Index (Vicente-Serrano et al., 2010) is a modified version of the SPI, using a simplified moisture balance of rainfall and PET. This index is chosen to assess the potential influence of including PET on drought prospects, as PET is set to increase. The calculation steps are therefore similar to those of SPI, with the input data being the difference between rainfall and PET. Drought categories are also kept the same as in Table 5-2. Similar to SPI, the calculation procedure of SPEI at scale *i* includes the following steps:

i) Prepare a dataset of monthly precipitation subtracted by monthly PET

ii) Calculate the moving average of the previous *i* months

iii) For each month, fit the data to a suitable probability density function such as the Gamma distribution, the log-normal distribution, the Gumbel distribution and the Pearson III distribution (there are 12 distributions representative of the baseline distribution of each month)

iv) Transform the probability density function into the standardised normal (Gaussian) distribution

v) Calculate the precipitation deviation away from the baseline distribution

To identify a suitable probability distribution for SPEI fitting, Vicente-Serrano et al. (2010) have used the L-moment ratio diagrams by Hosking (1990). “L” denotes Linear and the L-moment is linear combinations of order statistics. It is computed as the ratio of L skewness τ_3 and L kurtosis τ_4, which measures how skew to the left or right and how peaky the shape of the distribution is. As the ratio of these measures characterise different probabilistic distributions, they can be used to analyse whether the empirical data are close any of these distributions in terms of the L-moment ratio (Hosking, 1990). The diagram as such shows each group of distributions in conjunction to the L-moment ratio of the empirical data.

Figure 5.4 demonstrates the L-moment ratio diagrams of the RCM, FF and Observed monthly water balance data (which is monthly rainfall subtracted by monthly PET) in comparison to the Generalised Logistic distributions (GLO), the Generalised Extreme Value distributions (GEV), the Generalised Pareto distribution (GPA), the Generalised Normal distribution (GNO) and the PearsonIII distribution (PE3). In essence, the L-moment ratios were calculated for each month of the baseline 1961-1990 time series of the observed data, the FF and the RCM product. Each month of a time series is represented by an L-moment ratio, therefore becomes a point in the ratio diagram. As such, a time series will have 12 points representing the L-moment ratios of each month. This process was reiterated for the time series of the observed data and each member of the FF and RCM product. Visual analysis indicated that the L-moment ratios of the observed data, the RCM and the FF group do not strongly belong to any of the distributions. In this study, the log-Normal distribution was chosen for SPEI data fitting.

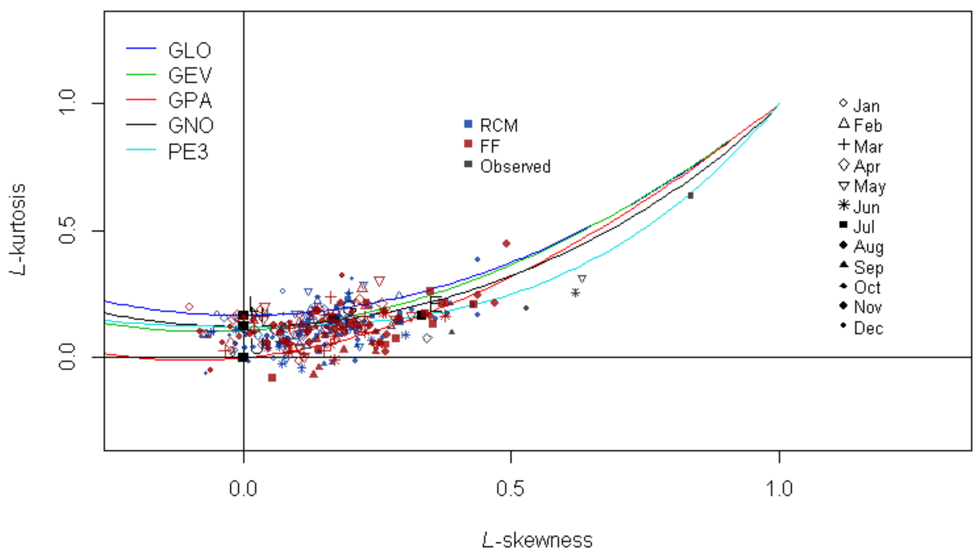


Figure 5.4 L-moment ratio diagram for the 1961-1990 baseline of Observed, RCM and FF time series of monthly data. The empirical values are shown against the theoretical L-moment ratios for Generalised Logistic (GLO), Generalised Extreme Value (GEV), Generalised Pareto (GPA), Generalised Normal (GNO) and Pearson type III.

5.2.3. Data and methods

5.2.2.1. The study catchment

The chosen study area is the River Rother catchment, which is a major surface water source of the Sussex water resource zone (Figure 5.5). Drought frequency of the catchment is calculated based on SPI and SPEI index for the pre-1961 period, the 1961-1990 baseline, the 2020s, the 2030s and the 2050s.

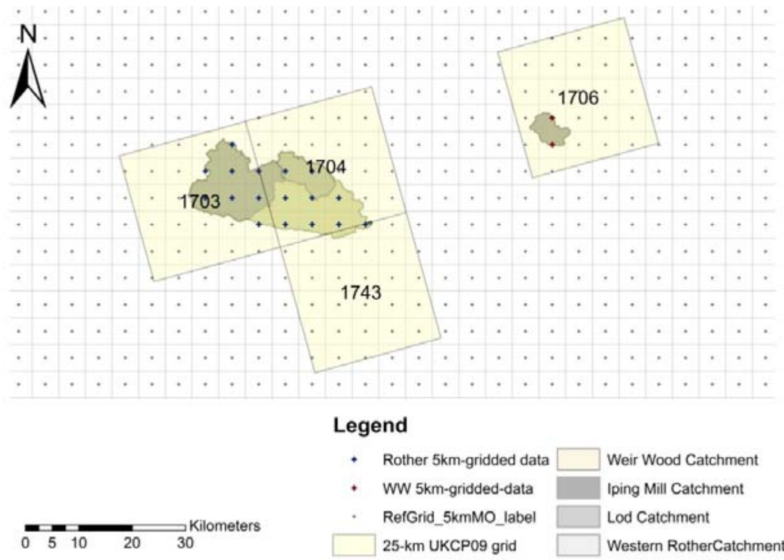


Figure 5.5 Catchments in the study area and available historic dataset

5.2.4. Historic data

There exist two available historic climatic datasets of the River Rother catchment: a weighted average of rain gauged data from Southern Water and a 5 km Met Office gridded data (Table 5-4). The former set contains daily PET and rainfall data, while the latter provides monthly temperature and rainfall data. PET was calculated using the Met Office Rainfall and Evaporation Calculation System (MORECS) (Thompson et al., 1981). A comparative analysis of rainfall data shows that the two sources are consistent (Figure 5.6). In this study, Set 1 thus was chosen as the Historic data set for analysis.

Table 5-4 Summary of available historic data

Historic data set	Source	Period	Type of data	PET available	PET calculation method	Rainfall available	Rainfall calculation method
Set 1	Atkins/ Southern	1888-2009	Point data	Daily	MOREC/ MOSES	Daily	Weighted values of

	Water						rain gauges
Set 2	Met Office	1914-2006	5 km gridded data	No	n/a	monthly	Weighted values of rain gauges

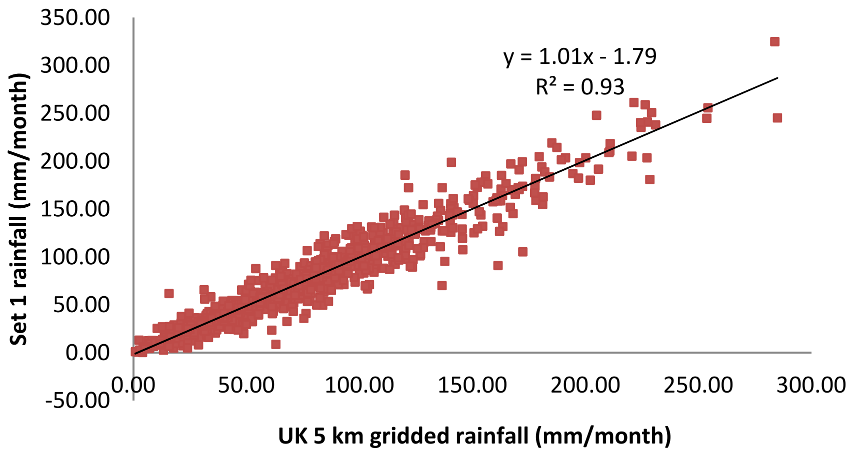


Figure 5.6 Comparison of two historic datasets

5.2.5. Potential evapotranspiration calculation

As the historic gridded dataset and three out of the four climate products do not provide PET, the study needs to deduce PET from available data of each product. Amongst the climate products, the historic (for the period of 1969 onwards) and RCM data have sufficient information for the FAO-56 reference Penman-Monteith equation (Allen et al., 1998).

$$PE\left[\frac{mm}{day}\right] = \frac{\left(\lambda^{-1}\Delta(\mathrm{R_n} - \mathrm{G}) + \gamma\frac{900}{\mathrm{T} + 273}\mathrm{U_2}(\mathrm{e_s} - \mathrm{e_d})\right)}{\Delta + \gamma(1 + 0.34\mathrm{U_2})}$$

Equation 5-1

With λ latent heat of vaporisation [MJ/ kg],

R_n net radiation at crop surface [MJ/ m^2 day]

T average temperature at 2 m height [Celsius degree]

U_2 wind speed measured at 2 m height [m/s]

e_s-e_d vapour pressure deficit for measurement at 2m height [kPa]

G soil heat flux [=0 MJ m^2 day]

Δ gradient of vapour pressure curve [kPa/ºC]

γ psychrometric constant [kPa/ºC]

900 coefficient for the reference crop in [kJ-1 kg ºK/day]

0.34 coefficient for the reference crop [s/m]

The historic dataset, SCPs and UKCP09 have to employ several temperature-based formulae to deduce monthly PET. These PET methodologies were tested against the historic dataset that contains PET data. Four PET methods were selected as follows

- Hamon method (Hamon, 1961)

$$PE\left[\frac{mm}{day}\right] = \left(\frac{N}{12}\right)^2 \exp\left(\frac{T}{16}\right)$$

Equation 5-2

With T being the average temperature (Celsius degree)

N the maximum possible daylight hours (h)

- Oudin method (Oudin et al., 2005)

$$PE\left[\frac{mm}{day}\right] = \begin{cases} \frac{1}{\lambda} S_0 \left(\frac{T+5}{100}\right) & if\ T > -5^0 C \\ 0 \quad otherwise \end{cases}$$

Equation 5-3

With λ being the latent heat of vaporisation [MJ/kg]

S_0 being extraterrestrial radiation [MJ/m2day]

- Guiness-Borne method (McGuinness and Bordne, 1972)

$$PE\left[\frac{mm}{day}\right] = \frac{\frac{1}{\lambda} S_0 (T+5)}{68}$$

Equation 5-4

- Thornthwaite method (Thornthwaite, 1948)

$$PE\left[\frac{mm}{month}\right] = 16\left(\frac{10T}{I}\right)^{a}$$

Equation 5-5

With I being the annual heat index

The Thornthwaite formula can further be corrected to take into account the variation due to latitude differences.

5.3.RESULTS AND DISCUSSION

5.3.1. Potential Evapotranspiration

On a monthly scale, the FAO-56 PET calculation of the Met Office gridded data (Historic data set 2) yields similar results to the MORECS PET of historic dataset 1 (Figure 5.7). This similarity is because both FAO-56 and MORECS are based on the Penmann-Monteith methodology and use similar input data, such as radiation, temperature and relative humidity.

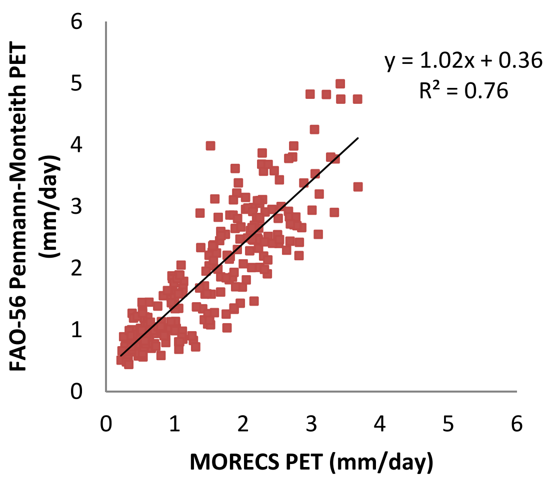


Figure 5.7 Graph of MORECS PET versus FAO-56 Penmann-Monteith PET

On the contrary, all four temperature-based methodologies exhibit systematic bias compared to MORECS PET (Figure 5.8). In the Rother catchment, temperature-based methodologies such as Hamon, Oudin, Guiness-Borne and Thornthwaite significantly underestimate PET compared to the MORECS and FAO-56 formulae. The disparity amongst the methods suggests that the formulae need to be re-calibrated for the catchment and the region. Furthermore, the Guiness-Borness formula produces negative PET values when the temperature drops below 5 ^{0}C and the Thornthwaite formula cannot calculate PET for below-zero temperature.

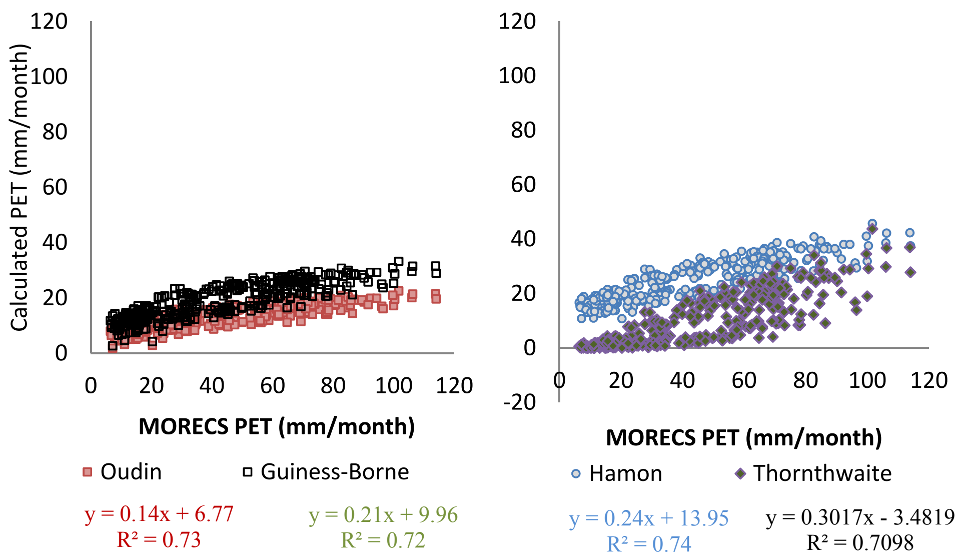


Figure 5.8 Comparison of temperature-based PET formulae against MORECS PET data

The study assumes that while underestimating PET, Oudin is capable of simulating PET changes based on the reference baseline PET. Moreover, PET comparison across time periods is likely to be valid if the methodology is consistent within each climate product, as the comparison is amongst its own PET time series across the time periods. For each climate product, the PET methodologies are thus selected as follows

- **RCM data**: The FAO-56 Penmann Monteith method was selected, since the projections provide sufficient input data for the method.
- **FF data**: PET is readily provided in the product. This product uses the FAO-56 Penmann Monteith to calculate PET.
- **Historic observed data, UKCP09 and SCP**: Amongst the PET methodologies, the Oudin method was selected, since it can work over a wide range of temperature and has a simple mathematical form for potential recalibration. In this study, such calibration was not conducted due to the time constraints. However, potential PET underestimation was acknowledged and taken into consideration in the analysis. While it is preferable to use the Oudin method across all of the three dataset, the analysis on historic data shows that the Oudin equation significantly underestimates PET. Thus the MORECS historic PET was chosen as the historic baseline PET, in order to reflect the true historic balance between rainfall and PET. PET changes due to increased temperature was then simulated using the Oudin equation. In essence, the Oudin equation assumes that PET changes with T as follows

$$PE\left[\frac{mm}{day}\right] = \begin{cases} \frac{1}{\lambda} S_0 \left(\frac{T+5}{100}\right) & if\ T > -5^0C \\ 0 \quad otherwise & \end{cases}$$

Equation 5-6

With λ being the latent heat of vaporization [MJ/kg]

S_0 being extraterrestrial radiation [MJ/m2day]

Assuming that S_0 and λ remain constant and all PE for temperature below -5 ^{0}C are 0, an increased PE due to increase temperature can be written as

$$PE_{change}\left[\frac{mm}{day}\right] = \begin{cases} \frac{1}{\lambda}S_0\left(\frac{T_{change}+5}{100}\right) & if\ T_{change} > -5^0C \\ 0 & otherwise \end{cases}$$

Equation 5-7

If we divide the first equation by the second equation, it follows that

$$\frac{PE}{PE_{change}} = \frac{T+5}{(T_{change}+5)}\ if\ T\ and\ T_{change} > -5^0C$$

As T_{change}=T(1+CF)

$$PE_{change}\left[\frac{mm}{day}\right] = \begin{cases} \frac{PE}{T+5}[T(1+CF)+5] & if\ T > -5^0C\ and\ T_{change}>-5 \\ 0 & if\ T_{change} < -5 \end{cases}$$

Equation 5-8

The formula does not work in the case of T< -5, as PE=0, it follows that PE_{change}=0 regardless of T_{change}. However, the monthly temperature time series of the Rother catchment does not contain any value below this threshold; the consideration of this case was thus avoided.

5.3.2. Analysis of the climate products

5.3.2.1. Comparison with observations

Two of the climate products (RCM and FF) were compared with past observations (Figure 5.9). Within the historic period of 1961-1990, the RCM runs already exhibit systematic bias. The RCM runs demonstrate drier July-November compared to the observations. Meanwhile, because of bias correction, the FF product has a nearly identical mean monthly precipitation to that of the observed data during the 1961-1990 period. However, this starts to weaken in the later time slices (there is a greater diverge between the runs), particularly in the 1981-2010 period when the observed rainfall in October is on average higher than the simulated values of both the RCM and FF products.

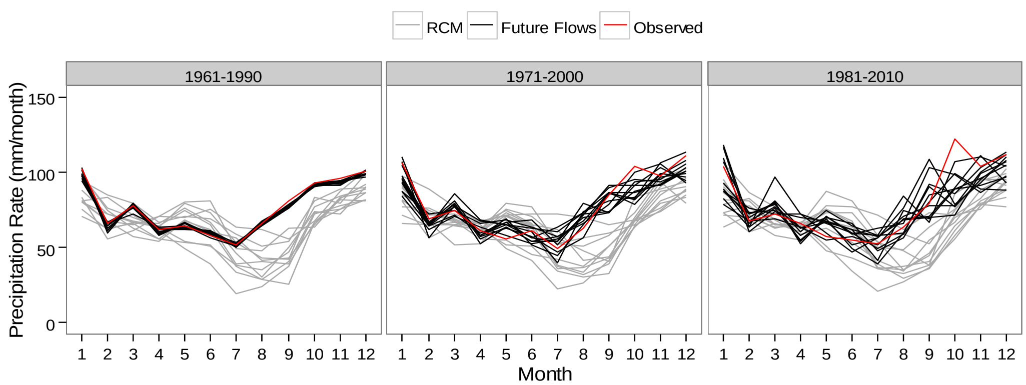


Figure 5.9 Comparison of observed rainfall with simulated rainfall from two climate products (RCM and FF) for different time periods (1970s, 1980s and 1990s) for the River Rother catchment.

Figure 5.10 then compares estimates of SPI for the period 1961-90 for observations and two climate products. Since the SPI transforms the baseline into a normal distribution of mean 0 for each month (which represents the climatological normal), the 1961-1990 observed data has become a horizontal line that overlaps the x axis. The average FF SPI is also very similar to the climatological normal, as this product has been bias corrected to match the observed data. The RCM data tend to overestimate short floods of 3-6 months in the early summer and underestimate drought risks in the late summer. SPI analysis on longer timescale generally reflect the total rainfall the catchment received during that period and how severe it is compared to the average baseline. Analysis on the annual and two-year drought scale show that both the FF and particularly RCM data underestimate the rainfall amount falling onto the catchment and therefore overestimate the risks of long droughts.

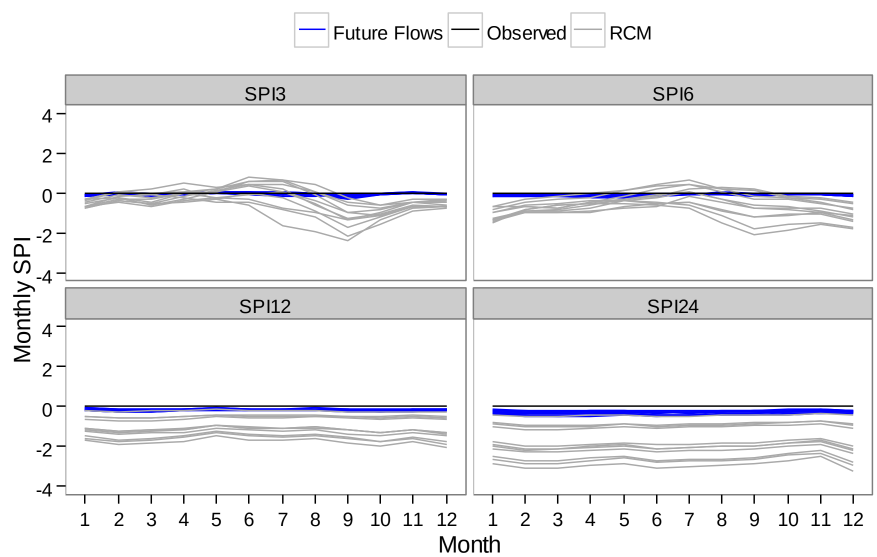


Figure 5.10 Standardised Precipitation Index (SPI) for multiple timescales (3, 6, 12 and 24 months) for two climate products (RCM and FF) and observations over the period 1961-1990.

5.3.2.2.UKCP09 and SCP: spatial coherence of climate data

As described in Section 5.2.1, the UKCP09 and the SCP dataset are two similar gridded products of the UK Climate Projections. Both of these products present climate projections as monthly change factors (Figure 5.11). Compared to the SCP dataset, the UKCP09 product samples a wider range of uncertainty, which enables adaptation studies to test adaptation strategies against a wider range of circumstances. Yet, due to the simulation design, each run of the UKCP09 grid is not consistent across its cells. On the contrary, the gridded results of each SCP run are spatially correlated and thus can be used for catchments that span more than one grid cell. Figure 5.11 shows that these dataset contain a wide range of possible changes for each month, with the SCP set having a slightly narrower band compared to that of the UKCP09. Due to the difference sampling strategies, the bound of these two set are different. While UKCP09 is considered to sample a wider range of uncertainty, it is acceptable that some of the SCP change factors are beyond the UKCP09 bound (Sexton et al., 2010).

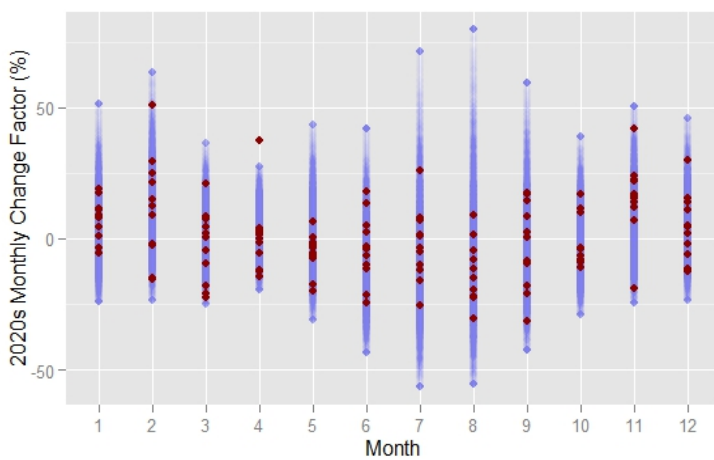


Figure 5.11 Comparison of the monthly rainfall change factors of UKCP09 (10,000 blue dots) and SCP (11 red dots) in the grid cell 1704 for the 2020s Mid-Emission climate scenario

Since the Rother catchment spreads across the grid cell 1703, 1704, and 1743, using the UKCP09 dataset can be potentially problematic as this set was not designed for cross-grid usage. Yet, an analysis of spatial correlation analysis amongst the SCP grid of the catchment shows that the change factors of the grids do not differ significantly; indeed, they even remain similar for the cell 1706, which is located further north and contains the Weirwood catchment (a reservoir of the water resource zone) (Figure 5.12). Furthermore, the historical trend and the projections of other climate products indicate that the area is relatively homogeneous in precipitation and temperature distribution: the Rother catchment and the Weirwood catchment historically received a similar monthly rainfall (per unit area) (Figure 5.13) and the temperature time series of these two catchments do not diverge considerably.

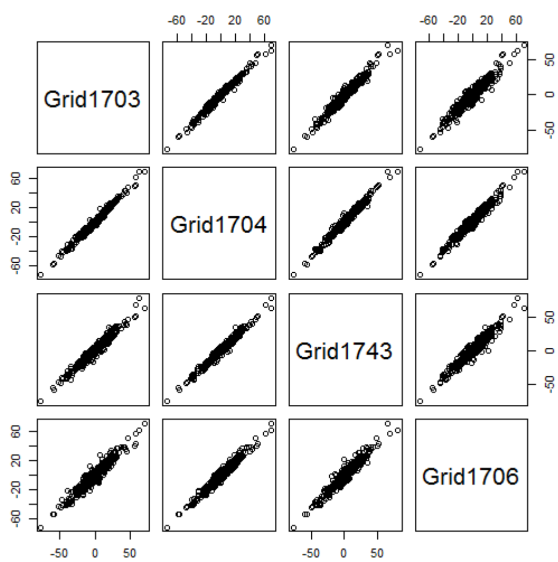


Figure 5.12 Comparison of precipitation change factors (5) in various SCP grid cells in 2050s

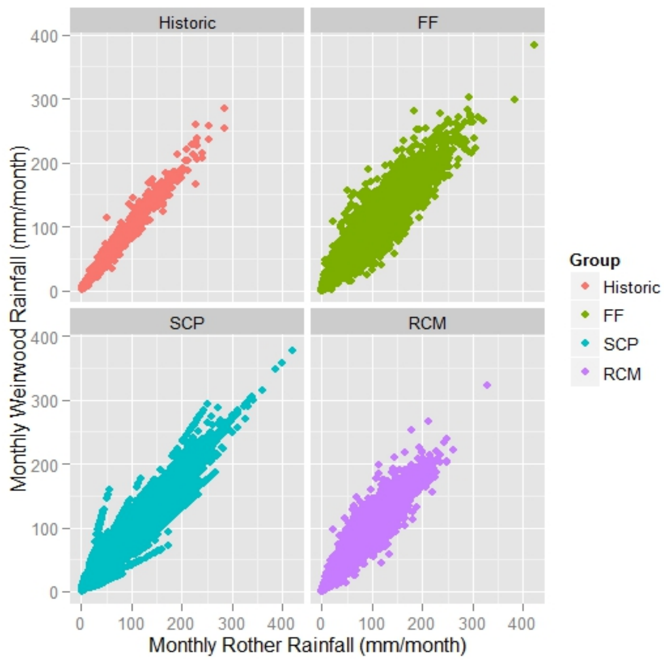


Figure 5.13 Correlation analysis of monthly rainfall received by the Rother catchment and the Weirwood catchment shows a consistent linear trend across time.

Due to its larger catchment area, the Rother catchment receives more rainfall than the Weirwood, but overall rainfall per unit area of the two catchments are similar. Data for the assessment were drawn from the 1914-2006 period (historic data), 1950-2099 (RCM), 1950-2069 (FF) and the 2020s, 2030s, and the 2050s (SCP).

As such, it is considered acceptable to use the UKCP09 change factors of one grid for the whole Rother catchment and the Weirwood catchment. In this study, the UKCP09 change factors of grid 1704 were used to represent the UKCP09 climate projections for the Rother catchment grids.

5.3.3. SPI and SPEI-based drought analysis

5.3.2.3.SPI versus SPEI: a comparison of the two indices

Overall, the L-moment analysis determines that the Gamma distribution is suitable for SPI fitting and the Pearson III distribution is suitable for SPEI. The study shows that SPI and SPEI are capable of indicating various drought events (which have negative SPI or SPEI values), including the severe events in 1921-1922 and 1975-1976 (Figure 5.14). A positive SPI or SPEI value shows that the condition is wetter than normal, while negative SPI indicates dryness. According to McKee et al. (1993), the monthly SPI values between -1.00 to -1.49, -1.50 to -1.99, and of -2 or less are subsequently classified as moderate droughts, severe droughts and extreme droughts. Aside from drought classification, these indices are able to demonstrate dryness on multiple timescales. For instance, the 1921-1922 drought was a two-year extreme drought (24-month SPI <-2) while the 1975-1976 drought was similarly severe on the 12-month scale but did not match 1921-1922 conditions over a long time scale. For this historic period, there is little difference between SPI and SPEI values: the difference between these two indicators remains close to zero. As SPI is precipitation-based and SPEI is precipitation and evatransporation-based, the similarity between SPI and SPEI for this period shows that rainfall is the dominant factor in creating droughts.

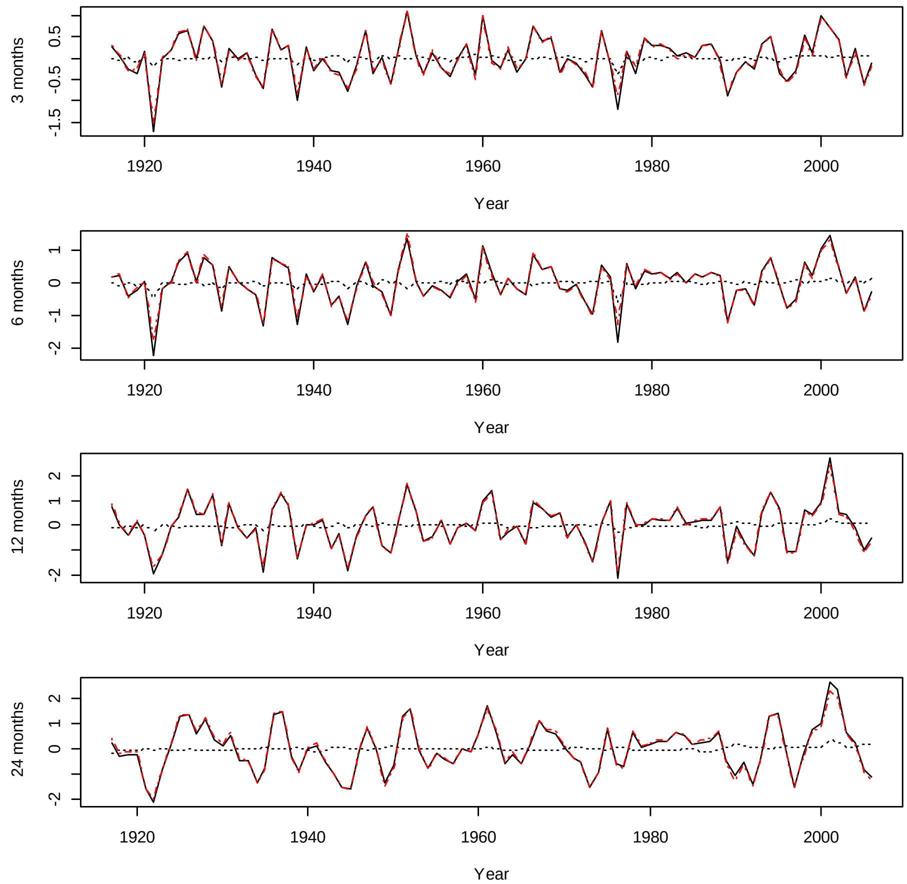


Figure 5.14 SPI and SPEI values of the 1914-2006 historic period. The SPI time series are indicated by the red line and the SPEI by the black solid line. The black dotted line shows the difference between SPEI and SPI.

Figure 5.15 shows the mean changes in 3-month SPI compared to a 1961-90 baseline (which has been standardised to zero) for observed data prior to 1961 and for all climate products for the 2020s, 2030s and 2050s. In comparison to the 1961-1990 baseline, the 3-month SPI of the 1914-1960 period shows less rainfall in the months of March to June and more rainfall from July to October. SPI projections for the 2020s, 2030s and 2050s show a gradually more pronounced seasonal pattern, with a drier April-to-November period. The shift in UKCP09 and SCP can be directly compared against the Pre-1961 as they share the same observed baseline; meanwhile, the changes projected by RCM and FF are with regards to their corresponding run in the referenced time period. Nevertheless, the relative changes in the average values of monthly SPI3 compared to their corresponding reference 1961-1990 baseline are quite consistent across the products. Changes of the RCM and the FF are highly similar, thus suggesting that the seasonal pattern and correlation were preserved in the FF downscaling process. The SCP product remains quite similar to the original RCM but exhibits some divergence, particularly in the summer of the 2050s. Compared to the other products, the UKCP09 data projects slightly less wet winters and less dry summers particularly in the 2050s.

All products show that the seasonal pattern will gradually become more pronounced with rising drought risk over time. By 2050s, the norm of an August or September month is likely to be shifted by -0.5, thus implying that a moderately mild drought of the 1961-1990 period will become the norm late summer state for that period. In comparison with the 1961-1990 baseline (average SPI/SPEI values of which are standardised to 0), the 3-month SPI shows that the 1914-1960 period generally receives less rainfall in the months of March to June while experiences more rainfall from July to October. Meanwhile, SPI projections of the 2020s, 2030s and 2050s show a gradually more pronounced seasonal pattern, with a drier April-to-November period.

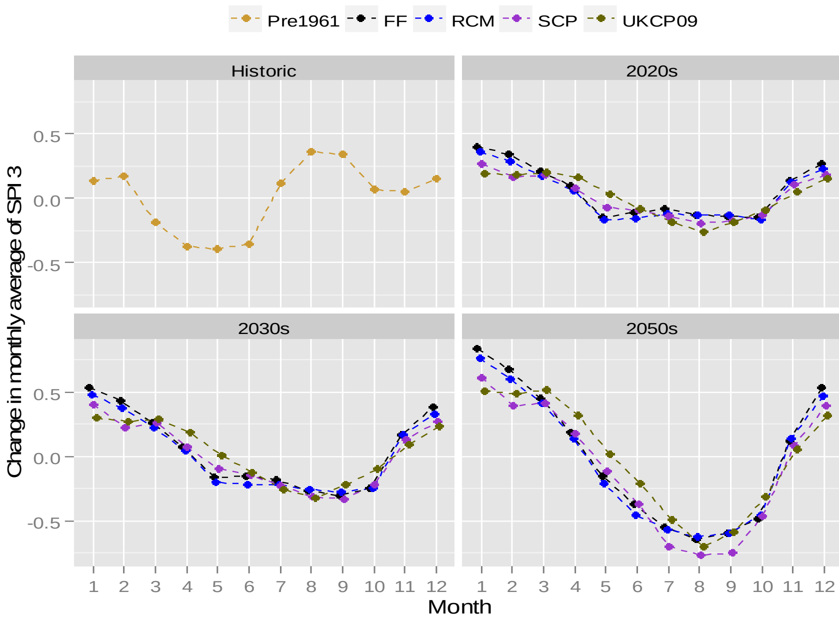


Figure 5.15 Average 3-month SPI changes across time periods based on the 1961-1990 baseline

However, when PET is taken into account, the difference between the 1914-1960 period and the 1961-1990 baseline period becomes slightly smaller (Figure 5.16). The average SPEI projections show a considerable drying from June to September. The difference between climate products can stem from two sources of uncertainty: i) the climate uncertainty range sampled by these climate products, and/or ii) the PET calculation method (the FAO-56 versus the Oudin method). Yet, the graph shows that there is little difference between the group of RCM and FF (which use the FAO-56 method) and the group of UKCP09 and SCP (which projects PET changes based on the Oudin method). The change in seasonal pattern is more pronounced if PET is taken into consideration; this suggests that increase PET will become a vital factor in determining drought prospects. Overall, the analysis of the

2020s, 2030s, and 2050s shows an increasingly drying trend over the summer, with rising drought risk over time. By 2050s, the norm change in SPEI in August or September is -0.5, which means a normal period for the 2050s is to the 1961-1990 period a slight drought period.

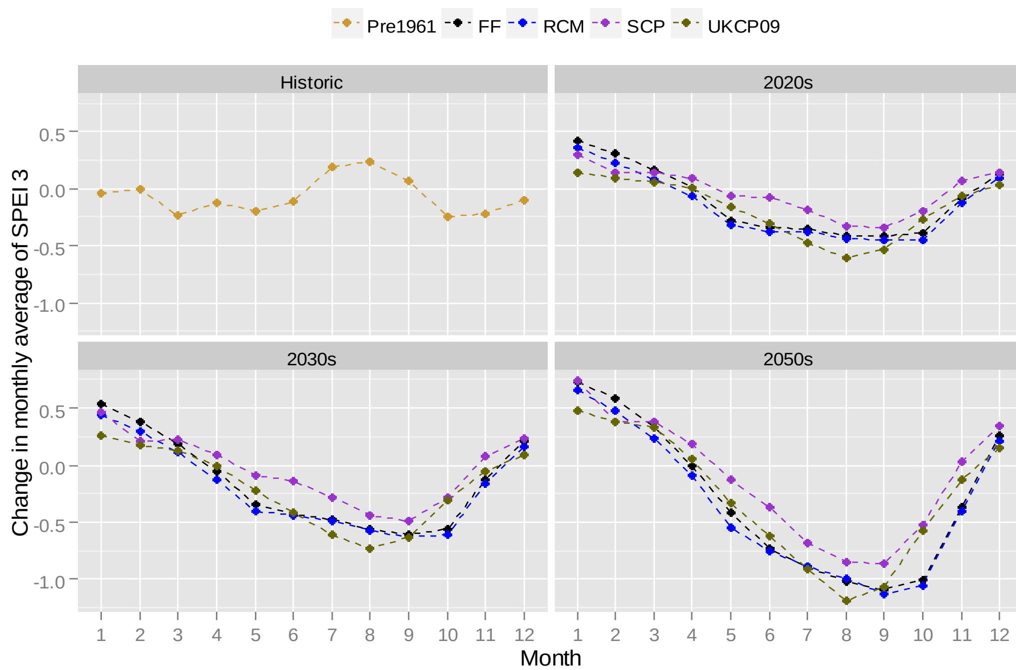


Figure 5.16 Average 3-month SPEI changes across time periods based on the corresponding 1961-1990 baseline. The baseline is the corresponding runs for the RCM and FF products, and the observed historic data for the UKCP09 and SCP products.

5.3.2.4.SPI and SPEI-based drought frequency analysis

Figure 5.17 to Figure 5.19 demonstrate the results of SPI-based drought frequency analysis and Figure 5.20 to Figure 5.22 demonstrate for SPEI-based drought frequency analysis. As described in Table 5.3, the moderate, severe and extreme drought months have a SPI or SPEI value from -1 to -1.49, The SPI-based results show that the 1914-1960 period has a higher frequency of moderate and extreme droughts than the baseline period. The relatively lower drought frequency of the baseline period suggests that the baseline period could have been extended to a longer period. A longer baseline period would have captured a wider range of drought types and magnitude, as droughts are rare extreme events. Climate products show large ranges of uncertainty in estimates of drought frequency, ranging from increases to decreases compared to observations. The uncertainty ranges are smaller for shorter duration droughts (such as 3 months) than for longer duration droughts (such as 36 months). In particular, the average trend projected by RCM and FF tends to be similar but with different impact ranges. For instance, the 9-month SPI of FF and RCM indicates a reduction of moderate droughts and significant increase of extreme droughts over the 2020s-2050s period, while SCP results indicate an increasing risk of moderate drought risks and a slow growth of extreme drought risk in 2020s-2030s and a sudden jump in 2050s.

Nevertheless, climate products generally project that the frequency of short droughts (3 months to 9 months) increases over time while the frequency of longer droughts is slightly less than that of the baseline period. The changes of drought frequency, however, are still relatively small with up to 5% increase in extreme droughts. Meanwhile, the graph shows that frequencies of the longer droughts do not increase compared to the baseline and the severe drought risks are even lower than the pre-1961 period. These figures also demonstrate the systematic differences among groups of climate products. In particular, the trend projected by RCM and FF tends to be similar, while SCP and UKCP09 results tend to agree with each other. For instance, the 9-month SPI of FF and RCM indicates a reduction of moderate droughts and significant increase of extreme droughts over the 2020s-2050s period, UKCP09 and SCP results indicate an increasing risk of moderate drought risks and a slow growth of extreme drought risk in 2020s-2030s and a sudden jump in 2050s.

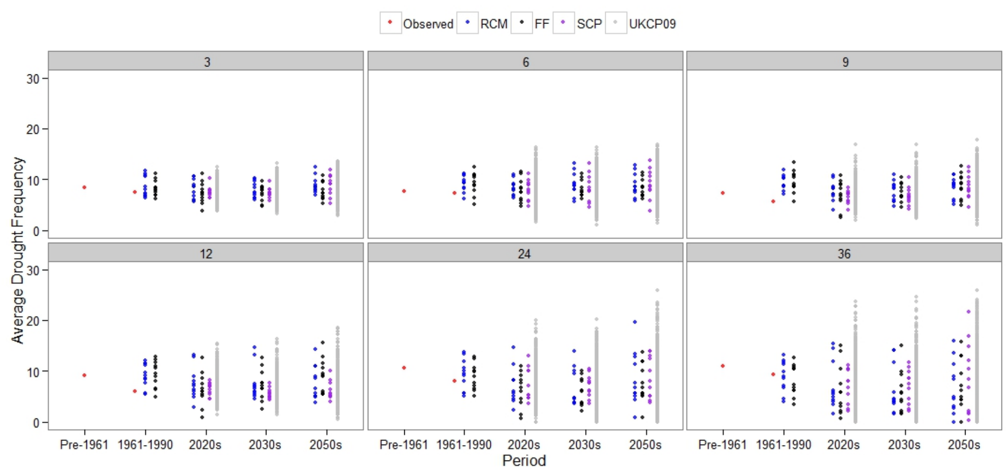


Figure 5.17 Average annual frequency (in percentage) of SPI-based moderate drought in different time periods (pre-1961, 1961-90, 2020s, 2030s and 2050s) according to different products (Observations, RCM, FF, SCP, UCKP09) for multiple drought durations (3, 6, 9, 12, 24,36)

The 24-month and 36-month SPI projects that the frequency of long-term droughts decreases compared to both the pre-1961 and the 1961-1990 baseline. On the contrary, there are increases of short-term drought, particularly in the summer months, due to the lack of precipitation. This can be explained by the calculation method of the SPI. The monthly precipitation is calculated as a moving average over several months. Therefore, longer term-based SPI will be calculated based on a long term average of precipitation. As the seasonal pattern of rainfall is set to become stronger, the summer months would be drier and winter months wetter than the baseline. The summer drought frequencies are subsequently rising. However, the longer term average of precipitation stays similar to that of the baseline, as increase winter rainfall compensates for the drying conditions over the summer.

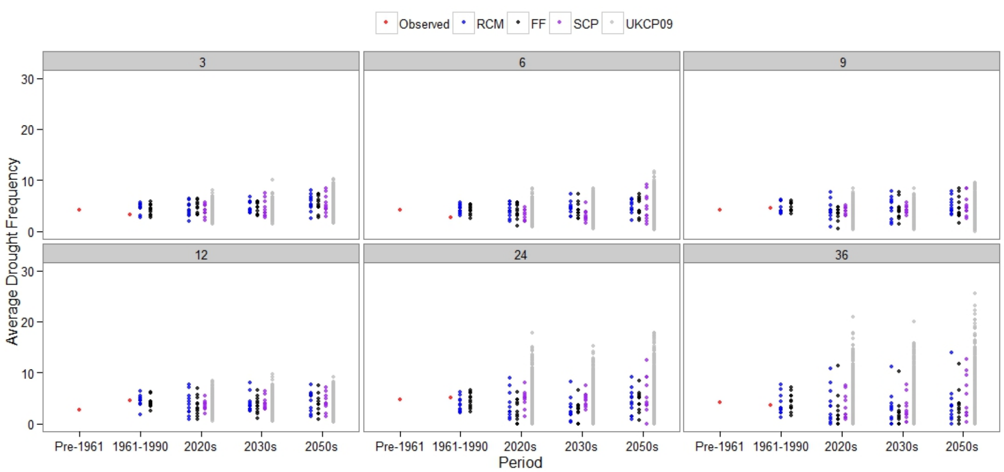


Figure 5.18 The annual frequency of SPI-based severe drought risks in different time periods according to different data sources

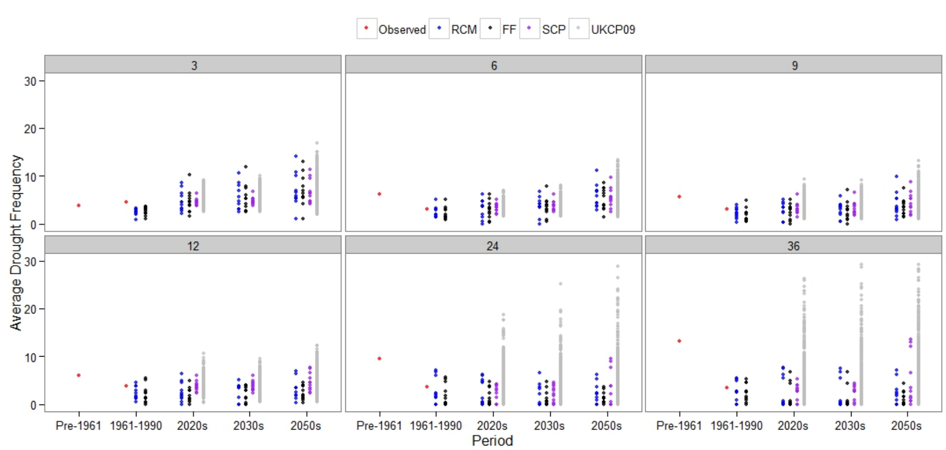


Figure 5.19 The annual frequency of SPI-based extreme drought risks in different time periods according to different data sources

In terms of SPEI, the overall drought frequencies based on SPEI are often higher than the drought frequencies based on SPI for the same climate product and time slice. Compared to the UKCP09 and SCP products, the SPEI-based drought frequencies for the RCM and the FF products tend to be lower regarding moderate droughts and higher regarding severe and extreme droughts (Figure 5.20 to 5.22).

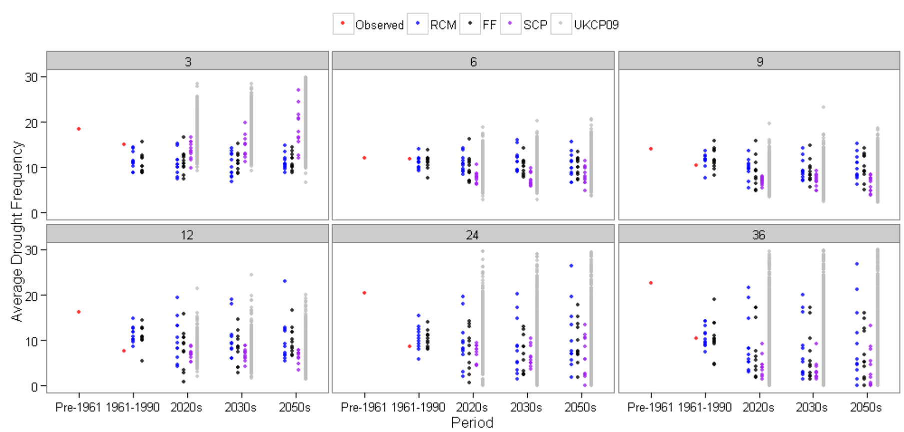


Figure 5.20 Average Frequency of Moderate Droughts according to the SPEI index on different time scale

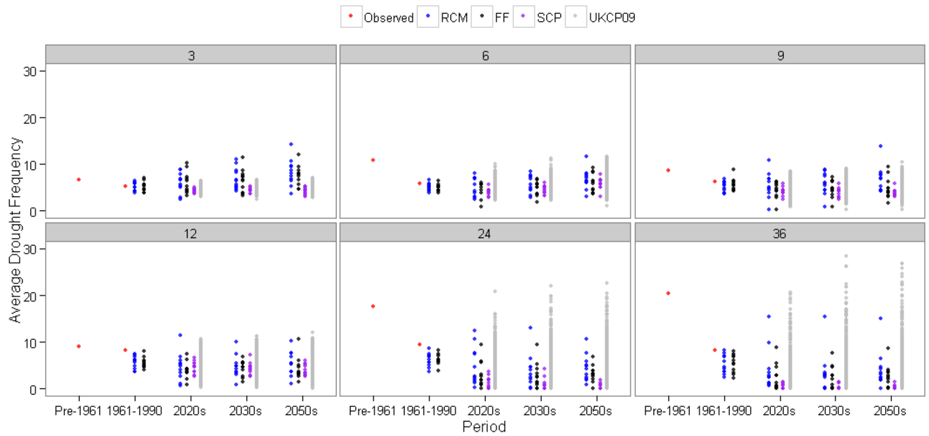


Figure 5.21 Average Frequency of Severe Droughts according to the SPEI index on different time scale

Similar to the SPI-based figures, the uncertainty ranges of SPEI-based drought frequencies are generally smaller for shorter duration droughts (such as 3 months) than for longer duration droughts (such as 36 months). The 9-month SPEI of FF and RCM indicates a consistent frequency but with an increased uncertainty range of moderate droughts and a slight increase of extreme droughts over the 2020s-2050s period, while SCP results indicate an decreasing risk of moderate drought risks and a gradual growth of extreme drought risk from the 2020s to the 2050s. Nevertheless, climate products generally project that the uncertainty range of short droughts frequencies (3 months to 9 months) increases over time. Meanwhile, the graph shows that frequencies of the longer droughts do not increase compared to the baseline and the severe drought risks are even lower than the pre-1961 period. However this could be an artefact as SPI and SPEI become less reliable in drought indication on a timescale of more than 24 months.

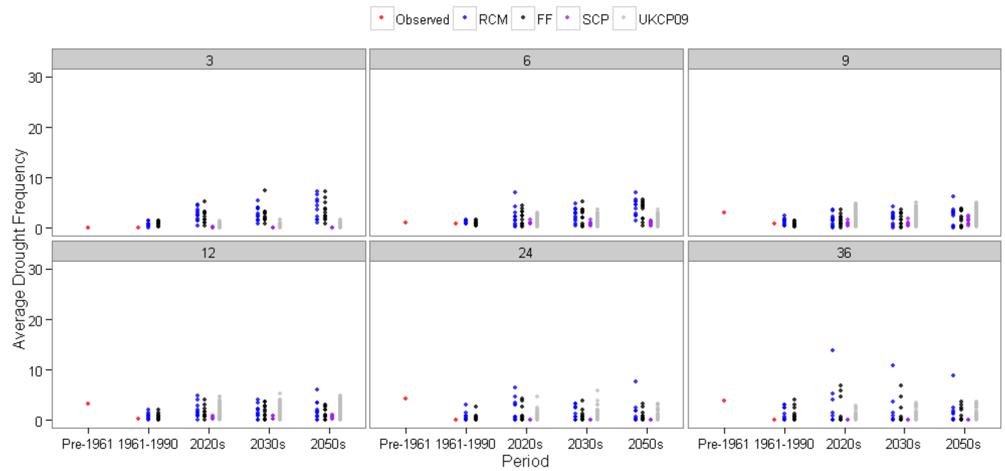


Figure 5.22 Average Frequency of Extreme Droughts according to the SPEI index on different time scale

As such, the drought projections of the 2020s, 2030s and 2050s show an enhancing role of PET, which can enforce droughts. When the role of PET is also taken into the equation, droughts are projected to increase in all durations. This demonstrates that the PET can become a driving factor of droughts. Almost all the climate products (except the SCP) demonstrate a growing risk of severe and extreme droughts in the 2020s to 2050s. While the 2020s are comparable to the pre-1961 period in terms of drought risks, the 2030s and the 2050s will experience a much higher drought risk. Compared to the precipitation-base SPI, SPEI projects a much stronger signal of changes. While the former projects a ±5% changes in drought frequencies, the latter shows up to 10% increase for the shorter droughts and 30% for the longer droughts. SPEI-based drought analysis shows a more considerable increase of drought risks, with a more pronounced intensification of extreme droughts due to increased PET. High PET further enforces precipitation deficiency, and therefore exacerbates drought risks. However, this risk could be mitigated by soil processes and changes in land cover.

The index of SPEI also demonstrates structural uncertainty amongst the climate products, with RCM projecting a relatively higher drought risk compared to FF, UKCP09 and SCP. On the contrary, FF, a bias-corrected product of RCM, shows a slightly lower change in drought frequencies. The risk and uncertainty envelope of extreme droughts appear to increase over time, with the 2020s period having similar drought frequencies to those of the 1914-1960 period. However, natural climate variability may still dominate the 2020s and 2030s, as Kendon et al. (2008) has shown that climate change signals can only be inferred with more than three 30-year projection periods. With SPEI, the systematic differences among the climate products persist. These differences might stem from three factors:

- The difference in sampled uncertainty of each climate product (as described in Table 5.1)
- The difference in the post-processing approach, such as bias correction, downscaling and resampling
- The difference PET calculation approaches, as the PETs of RCM and FF are Penmann-Monteith-based while PET changes of UKCP09 and SCP are Oudin-based
- Natural variability

Amongst all the considered climate products, SCP seems to consistently project the lowest change of drought risks while RCM produces the highest. It is noted that while RCM was known to significantly overestimate the drying condition, such bias was to an extent compensated by comparing changes within the same RCM runs. As such, although the historic RCM baseline (1961-1990) is drier than the observation data, the RCM future changes of drought risks is calculated based on the RCM baseline.

Finally, while the structural difference of the climate products are likely to cause the dissimilar drought projections, the results show that using different PET formulation within each climate product might affect the overall assessment. It should be noted that the Oudin formula was empirically derived from observations, which might not be similar to the conditions of the future climate. PET calculation for climate change therefore requires careful reconsideration if used beyond the calibrated range of climate. This is particularly the case of climate change studies, as the physical processes presented by the empirical equation might change, making the formula unsuitable. Furthermore, performance of empirical equations might shift in an unexpected way if the equations are used outside their calibration range. If the formula is to be use, it needs readjustment and recalibration, ideally using historic observations similar to the projected climate.

5.4.CONCLUSIONS

This chapter has applied two drought indices to analyse the drought pattern of historic periods and drought prospects in the 2010-2069 period. The study considers four UKCP-related climate products, which sample various uncertainty factors. Due to the lack of data inputs, two of these climate products do not supply PET values; consequently, the study also investigates various temperature-based PET methods. Overall, all the PET methods being considered underestimate PET if compared to the Penman-Monteith-based formulation. The Oudin method was chosen due to its simplicity and non-intensive data requirement. The monthly projected changes in drought frequency across these climate products did not show any bias introduced by using different PET methodology, as comparisons were made within each group of the climate products.

However, the annual statistic of drought frequencies shows a structural difference among the groups of climate products. This difference exists for both the precipitation-based SPI and the compound index SPEI. The differences in drought prospects according to these products are therefore due to inherent structural difference in the models and scaling process, although differences in SPEI statistics might also be the contribution of different PET equations. Drought analysis suggests that apart from a higher risk of rain deficiency, higher PET is increasingly an additional risk that exacerbates drought situation. Both SPI and SPEI exhibits increased frequency of severe and extreme droughts over the 2020s, 2030s and 2050s period.

Some of the projected drought frequencies are comparable to the pre-1961 period, thus suggest that the 1961-1990 period perhaps does not capture a wide range of drought conditions. As SPI and SPEI use this baseline to represent normal conditions, using a longer baseline might potentially lead to a fairer assessment of future droughts in comparison to historic droughts, such as to the worst drought of 1921-1922. Finally, the analysis shows that for the study area and a nearby catchment, the change factors of mean precipitation and temperature are highly spatially correlated. This correlation enables the study to use the UKCP09 product, which is not spatially coherent. However, the closely spatial correlation of change factors implies that drought risks build cumulatively not only over time but also over space, as droughts spread to the whole region.

Chapter 6. HYDROLOGICAL UNCERTAINTY

6.1.INTRODUCTION

Hydrological uncertainty has long been an important factor in water resource decision making (Wood, 1978). Coupled with climate change uncertainty, it can further widen the uncertain conditions for adaptation strategies. Hydrological uncertainty, including model structure, model parameters and natural variability, has been analysed in comparison with uncertainty from emission scenarios, Global Climate Model structure and downscaling methods (Boorman and Sefton, 1997; Fowler et al., 2007; Maurer, 2007; Kay et al., 2009). Wilby (2005) has shown that for sub-annual flow statistics, hydrological parameterisation uncertainty could be a major determining factor along with the uncertainty of the emission scenario; however it plays a limited role in determining the variations in annual mean flow quantiles. Meanwhile, following a conventional approach of cascading from Emission Scenario and Global Circulation Model to different downscaling approach and bias correction to hydrological models, Gädeke et al. (2013) and Chen et al. (2011) found that hydrological uncertainty could expand the uncertainty ranges; the largest source of uncertainty, however, is the choice of dynamic versus statistical downscaling approaches.

Regarding hydrological uncertainty, Brigode et al. (2013) demonstrated that selecting the optimal parameter set via a calibration period could bias the future hydrological projections towards flows under the climate characteristics of the calibration period. Yet, the relative magnitudes of climate uncertainty and hydrological uncertainty vary from catchment to catchment, and as such need to be analysed in the case study.

In the previous chapter, it has been shown that the four climate products of interest (UKCP09, SCP, the original runs of HadRM3 and their downscaled product done by the Future Flow project) project different changes in drought frequency for the 2020s, 2030s and 2050s. As such, apart from the climate uncertainty within each product, there is a post-processing uncertainty of the climate products. This post-processing uncertainty is of importance. They imply that the decision makers not only have to deal with the exploding uncertainty of translating climate projections into possible impacts, but also face uncertainty in choosing which product to use. In that context, the aim of this chapter is to further assess the uncertainty of climate projections when coupled with hydrological uncertainty. The chapter has three specific objectives as follow:

- To link meteorological droughts, as indicated by SPEI, with hydrological droughts indicated by low flows. As SPEI is a simple water balance model with no soil storage, a comparison between SPEI and the low flows will explore the role of soil storage in the catchment.
- To employ the Generalised Likelihood Uncertainty Estimation (GLUE) framework to explore the uncertainty of possible model parameterisation. GLUE differs from the classical calibration process in that it produces an ensemble of acceptable model characterisation rather than a single optimal one. As such, it enhances the likelihood of capturing future catchment behaviours under natural variability and climate change impacts.
- To use sensitivity analysis to assess the influence of parameter values on the calibration criteria and low flows in the calibration period and in the future time slices. This assessment will give more insight into inherent differences within the alternative parameterisation of GLUE and how these differences will project into the future. The knowledge of the dominant parameters under the projected conditions will facilitate future monitoring of changes and re-calibration of the hydrological model.

Section 6.2 will present the hydrological model CATCHMOD and two methodologies used in the study: the Generalised Likelihood Uncertainty Estimation method and Sobol

Global Sensitivity Analysis. Section 6.3 then analyses the results regarding the influence of model parameters and the interactions of climate uncertainty, post-processing uncertainty and hydrological uncertainty. The chapter concludes with Section 6.4, which summarises the key findings.

6.2.METHODOLOGY

6.2.1. The CATCHMOD hydrologic model

The Catchment Modelling model CATCHMOD is a water balance model initially designed for the Thames Basin (Wilby et al., 1994). The schematic of the model is presented in Figure 6.1. In contrast to the simple PET-rainfall balance of the SPEI index, water balance models such as CATCHMOD take into account water storages and percolation capacity of the soil. These are important factors in deciding catchment responses to rainfall events, as water can be retained in the subsurface zone, the underlying aquifers and at bank side storages, which then slowly release water even when the rain has ceased. The catchment model can consist of one or several contributing zones, each having the same model structure but with a different parameter set representing the zone attributes. The total catchment flows are then the sum of all contributing flows at the same time step.

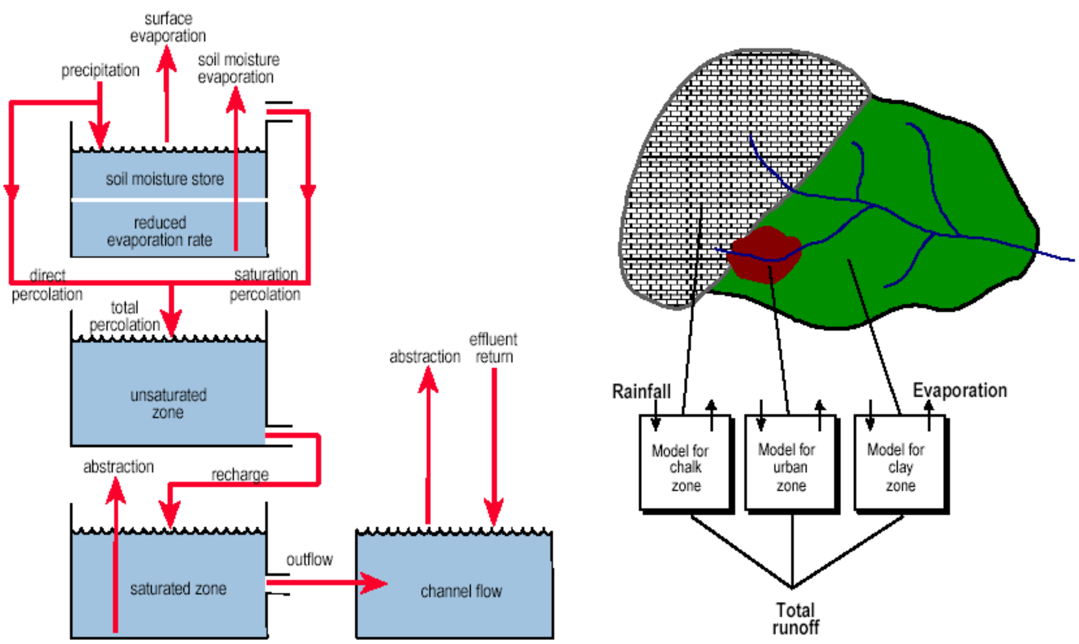


Figure 6.1 Schematic of the CATCHMOD model. **Source:** Wilby (2005)

CATCHMOD simulates catchment responses as a bucket system, in which soil storages are presented as interconnecting buckets. When the rain falls onto the ground, one part of the rain becomes run-off, some part of the rain slowly permeates the soil horizon while some are 'fast-tracked' into the lower soil zones via soil factures and microspores. In CATCHMOD, the direct percolation (DP) is a fixed proportion of precipitation, lost to the underlying zone via the latter process. Meanwhile, the water content of the soil surface can evaporate back due to evaporation. Yet, evaporation occurs at a reduced rate D_c (also termed Slope of the drying curve) if soil moisture deficit exceeds a threshold. This process reflects the increasing difficulty to draw water out as the soil becomes drier. CATCHMOD represents the soil moisture store as an upper and a lower zone, of which the upper zone is the first zone to dry up or get recharged. If the soil zone is saturated, the exceed rainfall further permeates the lower zone in the form of saturation percolation. Along with direct percolation, it forms total percolation. If the catchment overlays a permeable geological formation, this percolation passes from the unsaturated zone to the saturated zone and eventually becomes the base flow. This base flow is released at a non-linear rate back to the flows. Apart from the natural hydrological cycle, the water balance can be influenced by surface and groundwater abstraction, as well as effluent return and discharge from irrigation. These influences are directly subtracted or added at the relevant component, such as at the base flow or surface flow calculation. For more information on model equation, please refer to Greenfield (1984), Wilby et al. (1994) and Wilby and Harris (2006).

As such, there are two main differences of CATCHMOD flows compared to the SPEI model. In CATCHMOD, when rainfall exceeds PET, this excess does not directly turn into flows but some will be absorbed into the ground. While this process reduces the direct runoff, it is partially offset by the subsurface and base flow contribution. Therefore, a water balance model like CATCHMOD will have more 'memory' of the previous catchment states than the SPEI model of the same time step resolution. For instance, when PET is higher than rainfall, the SPEI model will result in no flows; meanwhile, CATCHMOD can still simulate subsurface flows originating from the past rainfall events.

In this study, this CATCHMOD model was chosen to represent the hydrological cycle of the Rother Basin, which has been described in Chapter 4. The catchment model is divided into six contributing areas representing the responses of different geological structures. This setting is based on the VBA Excel-based CATCHMOD model used by Southern Water and Atkins Consultants Ltd. Previous work of Southern Water and Atkins have identified certain parameter sets that perform well under the calibration period of 1990-1999 and the validation period of the 2000-2004 periods (Atkins Ltd., 2009). Model performances were assessed using the Nash-Sutcliffe coefficient, the R^2 and the mean squared residual of errors (MRSE). The Nash-Sutcliffe criterion is essentially R^2, but tends to $-\infty$ when the total residual error of the observation and the simulated values is worse than the total residual errors of the observations and their mean. Meanwhile R^2 is a piecewise linear function that is identical to the Nash-Sutcliffe coefficient in the positive zone and becomes 0 once the calculation returns negative values. Hoang et al. (2012) reassessed these criteria and found that while these criteria can indicate good model performance, each of these criteria orientates towards a different model behaviour. For instance, a model with a small mean residual error tends to have a good agreement in the large flows at the expense of the low flow errors, as an error in the high flows is often much larger and affect the MSE more than a lower error in the low flows. Meanwhile, the R^2 criterion, the square of the correlation between the observed flows and the simulated flows, tends to be more consistent in calibrating the low flow and the high flow period since each residual error is scaled proportionally to the observation. Nevertheless, both criteria are biased towards calibrating the high flow periods, as a good performance in this region can still significantly compensate poor performance elsewhere. In order to further enhance calibration in the low flow period, the study additionally employs the Nash-Sutcliffe criterion of the base-10 logarithm of the flows. For the purpose of the study, the VB.NET CATCHMOD model was translated into the Fortran90 language, which gives a faster performance as required for the number of runs. These VB.NET and Fortran90 versions were tested and yielded similar results to the 6^{th} significant number for flows in m^3/s.

6.2.2. The GLUE methodology and Sobol sensitivity analysis

Uncertainty and sensitivity analysis are two closely intertwined fields. The former field focuses on the uncertainty components of input data, the conceptual model and the parameter values; the latter provides useful methodologies to analyse how the variations in the model parameters can lead to changes in the outputs. In this study, two specific methods of uncertainty and sensitivity analysis were combined to explore the contribution of hydrological model parameterization to flow projections. Both of these methodologies are Monte Carlo-based and require many model runs; an efficient experimental design to conduct both of these analyses is therefore essential.

6.2.2.1.The GLUE methodology

The Generalised Likelihood Uncertainty Estimation (GLUE) methodology (Beven and Binley, 1992) uses a Monte Carlo sample of model parameters; it assumes the likelihood of model acceptability to be equivalent to the goodness-of-fit measure. This methodology emphasises that different model structures and parameterisation can produce an acceptable model performance (*equifinality*). It thus moves away from the traditional model calibration and validation process of selecting one optimal parameter set towards a new framework. This framework uses an ensemble of model structures and/or parameterization of satisfactory performance. The model ensemble is often termed the 'behavioural' group and is selected based on a user-defined goodness-of-fit threshold.

The outcome of GLUE is therefore several alternative representation of the catchment, instead of an optimal parameter set such as the outcome of the classical model validation process. The inclusion of several parameter sets thus is more likely to capture the process under different conditions. For hydrological models, using GLUE produces several parameter sets that capture the varying flow conditions, in contrast to the dilemma of choosing an optimal parameter set; this is particularly beneficial if the model parameter sets are not consistently optimal across different calibration periods or criteria (Freer et al., 1996). Under a changing climate and hydrological regime, using GLUE is valuable since the inclusion of more parameter sets might increase the possibility of the model being able to perform despite these changes.

Yet, in such cases, the use of GLUE may also raise certain issues. Firstly, while distinct parameter sets may produce converging results in the calibration period; under a different time period and conditions, simulation results of such sets may diverge and thus project different possibility of changes. If in the calibration period such differences can be crosschecked with the observed flows, in the future there is not yet any data to validate the 'goodness-of-fit' of these projections. While the variations in the GLUE projections, termed the 'equifinality' uncertainty (Beven and Freer, 2001; Beven, 2006), are often assessed as a total term, there is a need to test whether distinct trends exist within the overall equifinality uncertainty. Secondly, the future influence and the interactions of the 'behavioural' parameter sets on the model outputs might be different from the calibration period, thus affecting the overall likelihood of approximating the true catchment behaviour. For instance, assuming a 'behavioural' CATCHMOD parameter set was selected due to its capacity to simulate flows in intense convective storms; the parameter set has a small direct percolation rate that is representative of the soil condition in the calibration period. However if a drier condition would dominate the future period, the soil then develops more cracks and macropores and thus facilitates more direct percolation. As such, the parameter set is no longer representative of the catchment conditions and will produce errors in the flow projections.

A closer inspection highlights a common issue of these two concerns. To date, many principles in hydrology studies are based on the assumption of a single stable equilibrium state, which the term 'equifinality' seems to suggest. This assumption is evident in the common usage of a 'warm-up' period, in which a model is run for a certain period to reduce the uncertainty due to different initial conditions. Yet, Peterson et al. (2012) has shown that with the same parameter set, different initial conditions can lead to multiple steady states in several hydrological systems. This thus demonstrates the sensitivity of model and possibly catchment behaviour under different starting conditions. In the case of the GLUE ensembles, considering that the ensemble consists of different parameter sets, which subsequently produce different starting conditions in each time step, these differences can cumulatively lead to totally different catchment behaviours in the future projections. Furthermore, even within the calibration period, their similar and 'behavioural' goodness-of-fit does not indicate that the sets represent the same catchment response. Several works on GLUE (Wilby, 2005; Cloke et al., 2012) have demonstrated that model performance changes seasonally, thus suggest that some of the model is only representative of a certain condition and period. There subsequently exists a need to further inspect the group of 'behavioural' models to analyse the alternative states that they represent.

6.2.2.2. Sobol Sensitivity Analysis

Consequently, it is essential to conduct sensitivity analysis in order to understand the interactions and influence of the parameters on model performance and outputs. In the calibration period, sensitivity analysis will contribute towards understanding how different parameter sets converge to similar outcomes. For the future period, it provides hints of which parameters may become more influential; additionally, knowledge of the sensitive parameters will allow further monitoring of the changing conditions. Such assessment may shed light on the possible causes and the implications of such changes. In this study, the Sobol's global sensitivity analysis method (Sobol', 1990; Sobol, 1993) was chosen, with the scope of the analysis being the influence of a single parameter and the combined influence of each parameter pairs. Similar to GLUE, Sobol is a global sampling scheme to avoid oversampling around local minima or maxima. The Sobol methodology assumes that the total variance of the model output is contributed by the variance due to each single parameter (such as V_i, V_j, and V_k with i, j and k being the corresponding parameters) and the interactions amongst the parameters (denoted V_{ij}, V_{ijk}). Mathematically, if the input parameters are independent, this variance decomposition can be presented as

$$V = \Sigma_{i=1}^{k} V_i + \Sigma_i \Sigma_j V_{ij} + \Sigma_i \Sigma_j \Sigma_k V_{ijk} + \cdots + V_{1,2,\ldots,k}$$

Equation 6.1

The Sobol Sensitivity indices are the ratio of the variance of each component and the total variance. As such, dividing both sides by V, Equation 6.1 becomes

$$1 = \Sigma_{i=1}^{k} S_i + \Sigma_i \Sigma_j S_{ij} + \Sigma_i \Sigma_j \Sigma_k S_{ijk} + \cdots + S_{1,2,\ldots,k}$$

Equation 6.2

The number of the parameters considered in each sensitivity index is termed the order of the index. For instance, the first-order sensitivity index S_i denotes the sensitivity of the output to changes in input *i* while the second-order S_{ij} is the sensitivity due to the interaction of input *i* and *j*. The total effect of a parameter *i*, the sum of all sensitivity indices concerning *i*, is termed the total effect T_i. Often, these indices are not analytically derived due to model complexity; the concerning indices are subsequently approximated via a Monte Carlo sample of the model runs. To date, there have been several proposed calculation methods, such as Saltelli (2002), Sobol et al. (2007) and Jansen (1999). As the formulation varies, the specific required number of samples also vary. The Sobol' (1990) scheme requires two equal-sized sets of independent samples X_1 and X_2 in order to calculate the first-order indices. Assume that *k* parameters are considered, each sample set will have the size of *k* x *N* with N being the sample size. For a parameter *i*, the variance that *i* contributes to the model output can be estimated by comparing model outputs of X_1 and the same outputs when values of the parameter *i* are replaced by the X_2 values. While Saltelli et al. (2010) have summarised and proposed a less computationally expensive sampling and calculation design, those formulae only estimate the first and total sensitivity index. Therefore, in this study, the classical Sobol's method was selected. The study used the R sensitivity package (Pujol et al., 2013) which includes the Sobol (1993)'s method. In order to enhance the sample, the Latin Hypercube sampling technique was further used. This method ensures that the sample is more evenly distributed across the equal-probability sampling grid (Saltelli et al., 2000). In this study, parameter sampling and subsequent sensitivity analysis was conducted using R while the model ran in Fortran90.

6.2.3. Experimental Design and Input Data

6.2.2.3.Input data

Model parameters: The sampling parameters include five soil moisture storage parameters, two catchment storage parameters and two initial conditions of the CATCHMOD model (Table 6-1).

Table 6-1 CATCHMOD parameters and the sampling range

Soil moisture store parameters	Units	Descriptions	Denotation	Sampling range
Slope of Drying Curve		Usually 0.3 for most zones, zero for urban (paved) areas	Slope	0-0.3
Drying Constant (mm)	Mm	Finite storage of upper soil moisture store. Typically 30 to 150 (0 for urban).	PDC	0-150
Direct Percolation (%)	%	% bypassing soil moisture store. Typically 15 to 25 for aquifers, 0 for others.	DP	0-25
First (linear) storage constant.	Days	Typically 0 to 30	Cr/Phi	0-30
Second (non-linear) storage constant.	$m^3.days^2/km^2$	Typically 0 to 5000	Cq	0-5000
Initial output of first storage	mm/d	Initial condition.	R1	0-100
Initial output of second storage	m^3/s	Initial condition.	Q1	0-5
Upper Zone (one) Deficit	mm	Initial condition. Has a maximum value equal to the drying constant	D1	0-100
Lower Zone (two) Deficit	mm	Initial condition. Lower zone is effectively infinite	D2	0-100

The sampling ranges were based on the CATCHMOD guide included in the original Excel-based CATCHMOD model. In this version the catchment is divided into six contributing zones, labelled as Chalk, two areas of Greensand, one Clay area and two fast responding zones. The areas of these contributing zones are 78 km^2, 80 km^2, 50 km^2, 102 km^2, 10 km^2 and 15 km^2, respectively. From now on, they will be denoted as sub catchment 1 to 6 as outlined in Table 6-2. As such, the largest sub catchment is the Clay area, followed by the Greensand 1 and Chalk zone. Table 6-2 also demonstrates the currently optimal parameter set calibrated by Southern Water based on the Mean Residual Squared Error (MRSE), which has a four sub-catchment composition. The record of subsequent attempts shows a further break down into six sub-catchments but without any calibration improvement. This study, however, will keep this six-zone configuration to test whether it introduces any improvement if comprehensively sampled.

Amongst the parameters, the contributing area of each zone is kept constant. Despite the different geological characteristic of these areas, there is no explicit instruction on the range of the parameters. Therefore, parameter samples of each contributing zone were taken from the full range. The sampling distribution is assumed to be a uniform distribution ranging from 0 to 1 and scaled to the range of the corresponding parameters, as conducted in Cloke et al. (2010a). As there are six contributing zones and nine parameters for each, there are in total 54 parameters to be sampled.

Table 6-2 Original CATCHMOD parameters and contributing zone characterisation

Sub catchment	**1**	**2**	**3**	**4**	**5**	**6**
Area Type	Chalk	Greensand	Clay	Rapid	Rapid2	Greensand 2
Slope of Drying Curve	0.3	0.3	0.30	0.3	0.3	0.3
Drying Constant (mm)	130	30	20	0.5	0.5	30
Direct Percolation (%)	25	15	0	0	0	15
Upper Zone (one) Deficit	0	0	0	0	0	0
Lower Zone (two) Deficit	0	0	0	0	0	0
Area	**78**	**80**	**102**	**10**	**15**	**50**
Cr	30	25	0	0	0	25
Cq	2500	1500	10	0	0	1500
R1	0	0	0	0	0	0
Q1	1.5	0.75	0.5	0	0	0.75

Rainfall and PET data: The chosen catchment of this section is the River Rother. Rainfall and PET data are the same data used in the previous chapter, using the outputs of the four climate products of the UK Climate Projections 2009, UK Spatial Coherent Projections, the original Regional Climate Model and the downscaled product of the

Future Flows Project. The assessed time periods are the historic period of 1961-1990, the 2020s, 2030s and the 2050s.

6.2.2.4.Experimental design

The study uses two sampling sets to investigate the parameters

Sample 1-GLUE based analysis: 500,000 CATCHMOD runs using randomly generated parameters were tested against two model settings: one with only one contributing zone and another using the original structure of six contributing zones. The purpose of this sampling scheme is to identify the 'behavioural' group of parameters and conduct a preliminary assessment of parameter influences on model performance.

Sample 2-Sobol based analysis: 148,600 CATCHMOD parameter sets were constructed from two Latin Hypercube sample sets X1 and X2. These 148,600 sets enable the estimation of Sobol sensitivity indices up to the second order. Each set consists of 100 sets of values for the 54 parameters. The Sobol test set was constructed by iteratively replacing one or two vectors of X2 by the corresponding vectors of X1. The comparison between model outputs of X1, X2 and the adjusted X2 can produce an estimation of the first and second order sensitivity indices of each parameter. It should be noted that this experimental design only enables an estimation of the indices. As such, the larger number of samples contained in X1 and X2, the more reliable the estimations are. Yet, due to time and computational constraints, the number of sampling sets in X1 and X2 were kept at 100; the weak estimation power was partly compensated by using the Latin hypercube sampling and 100 bootstrapping scheme. Yet, there is still an uncertainty in these estimations.

Due to the large number of sets and computation constraints, it was not possible to run either the 500,000 or 148,600 set on all the climate products. The Future Flows product was thus chosen as the testing product of Sobol sensitivity indices. For all other sets, the behavioural sets of Sample 1, which are less time and computational extensive than the full 500,000 runs, were used.

6.2.2.5.The efficiency criteria

In this study, the Nash-Sutcliffe coefficient of daily flows and the base 10 logarithm of the daily flows were used. Additionally, the lowest total 7-day flows and the highest one were also considered in order to further assess the influence of parameter values on the flow projections.

In the historic period of both the GLUE and the Sobol experiment, the calibration period is the 1990-2004 period. In the future period, as there is no historic flow, only the lowest and the highest total 7-day flows are calculated over the whole period.

6.3.RESULTS AND DISCUSSION

6.3.1. The effect of soil storage on flows: Comparison of observation and SPEI

As previously discussed, SPEI is based on a simple water balance model of precipitation subtracting potential evaporation. In reality, not all potential evaporation can become actual evaporation. The catchment also responds more slowly than the SPEI model, due to the effect of flow retention in soil storages. While not considering the effect of soil storage, SPEI can have some 'memory' of previous month if calculated on a longer period. As SPEI is calculated as a moving average over that period, the two-month SPEI, for instance, can be affected by the rainfall-PET balance in the previous month. Therefore, SPEI can reflect to a certain extent the retention effect, in a similar manner that the autoregressive model considers the lagging effect of the past events. Yet, that lagging effect is not uniform over the year. Figure 6.2 demonstrates that while the correlation between SPEI and the actual flows are strong in the wet season, that correlation is much weaker during the drier months of May to August.

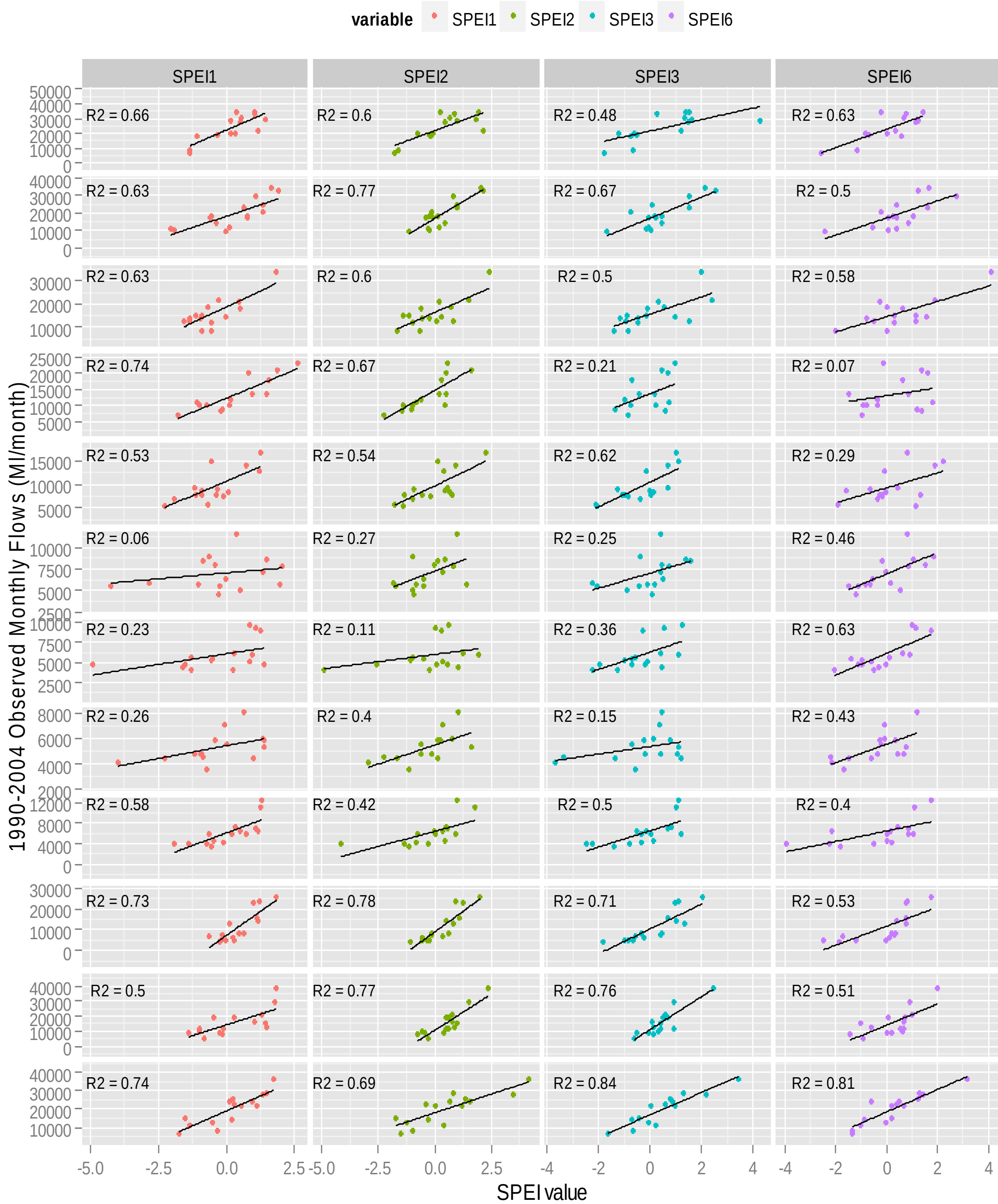


Figure 6.2 Graph of one-month, two-month, three-month and six-month SPEI versus Rother observed monthly flows (1990-2004) from January to December (right axis).

For dry months, flows are mostly retained water from the wetter period and thus do not directly related to the monthly SPEI. This that explains why the SPEI calculated over a longer period has more predicting power. Therefore in view of drier summers in the future, the summer flows will be increasingly dependent on winter storage. During the dry season, flows appear to correlate to six-month SPEI, thus suggesting that flows in these months are strongly controlled by rainfall input of the previous months. The figure also demonstrates the linkage between meteorological droughts and hydrological droughts, as well as the seasonal flow pattern of River Rother. Nevertheless, SPEI is relatively consistent in indicating low flows, for instance, a -2 SPEI in August generally indicates a monthly flow of 4000-5000 Ml/month.

6.3.2. The ranging low flows of the 'behavioural' group

Results of the GLUE analysis indicate that the number of contributing zones is an important factor to improve the simulation. The 500,000 parameter sets returns no 'behavioural' set if the whole catchment is configured as one contributing zone; meanwhile the six-contributing-zone structure produces 131 parameter sets. The 'behavioural' sets were model parameter sets with Nash values of 0.6 or above and log Nash values of 0.5 or above. Yet, within this group, there is an approximate variation of 8 Ml/day in Q99 and higher in the high flows.

Figure 6.3 shows a part of the flow duration curve, with x-axis being flipped in order to magnify the low flow part. As it demonstrates, the low flows of the ensemble range from 12 to 20 Ml/day. The higher projections of the ensemble also have a higher log Nash value, which indicates a better fit in the low flow part. Yet, the ensemble also demonstrates a certain non-converging behaviour, with two parameter sets producing a distinctively wetter projection than other sets.

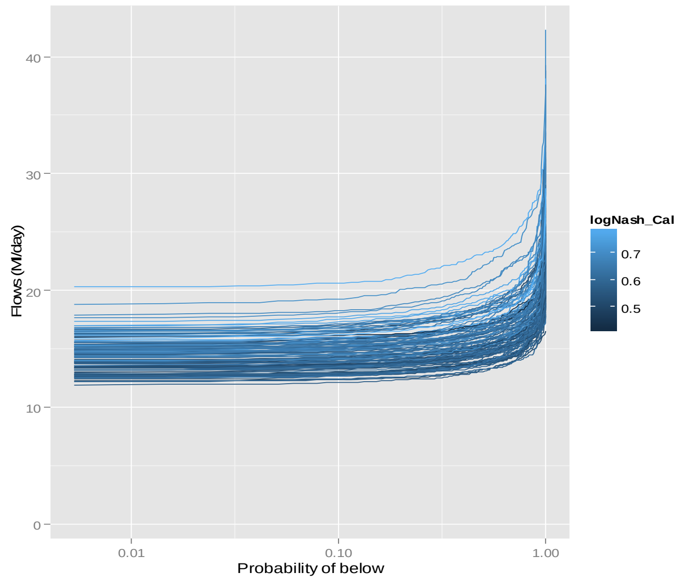


Figure 6.3 The ranging low flows in the behavioural group

The results of Sample 2 (the Sobol sets) further show variations in the simulated low flows (Figure 6.4). As the sampling set is smaller than the GLUE set, the number of the behavioural models is much smaller, with only one set having both Nash and log Nash higher than 0.6 and 54 sets higher than 0.5. The close correlation between the Nash and log Nash criterion is again demonstrated: the models having high Nash value also tend to have a high log Nash value. A comparison of the ensemble in terms of the lowest total 7-day flows shows that the models with higher log Nash (which means they are relatively better than other models in simulating low flows) usually have a smaller low flows than the rest of the ensemble. Overall the models with a log Nash value of over 0.5 tend to simulate around 750-1000 Ml/ week in the driest period.

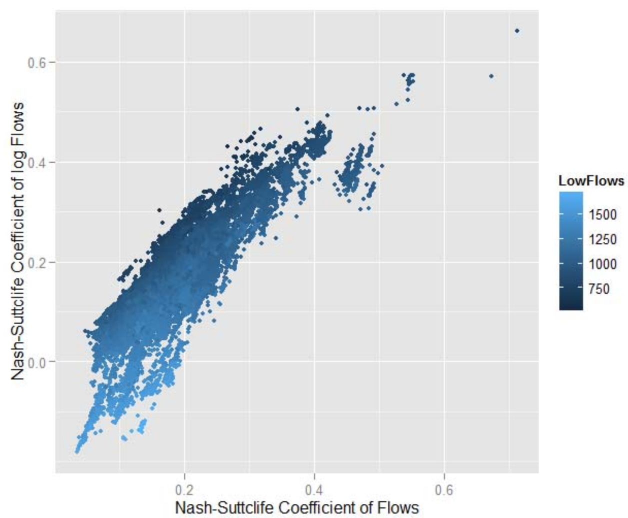


Figure 6.4 Graph of Nash coefficient versus log Nash of the Sample 2

Within each product group, the trend of changes across the time periods is fairly consistent. Amongst the members of the Future Flows climate product (Figure 6.5), hadrm3q14 and hadrm3q8 project a wetter trend in the low flows in 2020s and 2030s, but with a dramatic reduction in 2050s. Meanwhile other RCMs (Figure 6.6) exhibit a gradual decline of low flows. Compared to the non-downscaled original RCMs, the trend of changes in each member remains similar; however, it appears that the downscaling process of FF has made the trend less extreme. The most severe drying trend of FF is exhibited in the 2050s in hadrm3q13 and hadrm3q14, at approximately -75 Ml/d while in the RCM group, the most severe one is -120 Ml/d as projected by hadrm3q13 in the 2050s. Furthermore, Figure 6.5 and Figure 6.6 show some seemingly outliers in the changing trend, with certain hydrological projections are markedly different from the other members of the ensemble (same grid box).

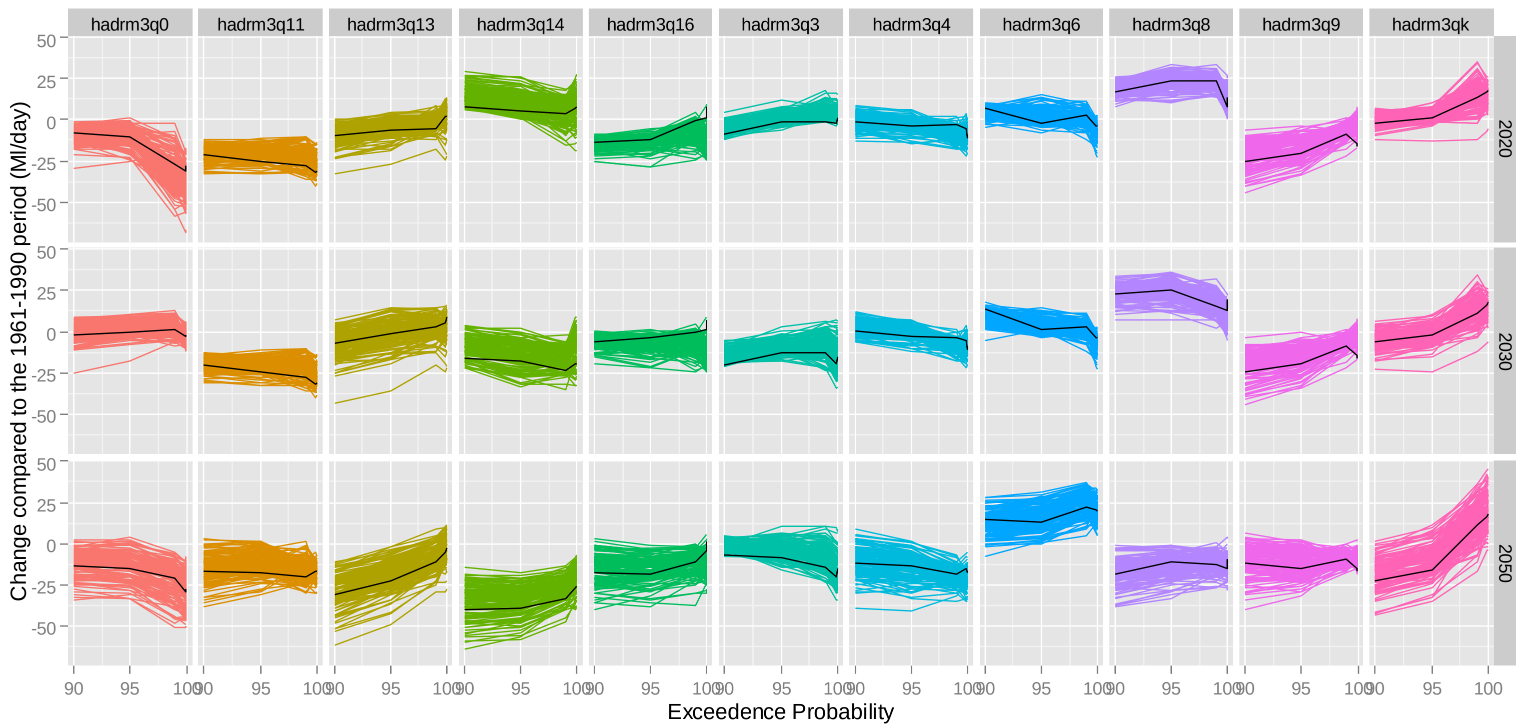


Figure 6.5 Changes of Q90, Q95, Q99 and Q99.99 compared to the 1961-1990 period in the FF climate product. Each line is one hydrological run out of the 131 behavioural CATCHMOD parameter sets. The black line shows the Nash 'optimal' parameter set of the GLUE ensemble, in order to compare the results of GLUE versus the classical calibration process.

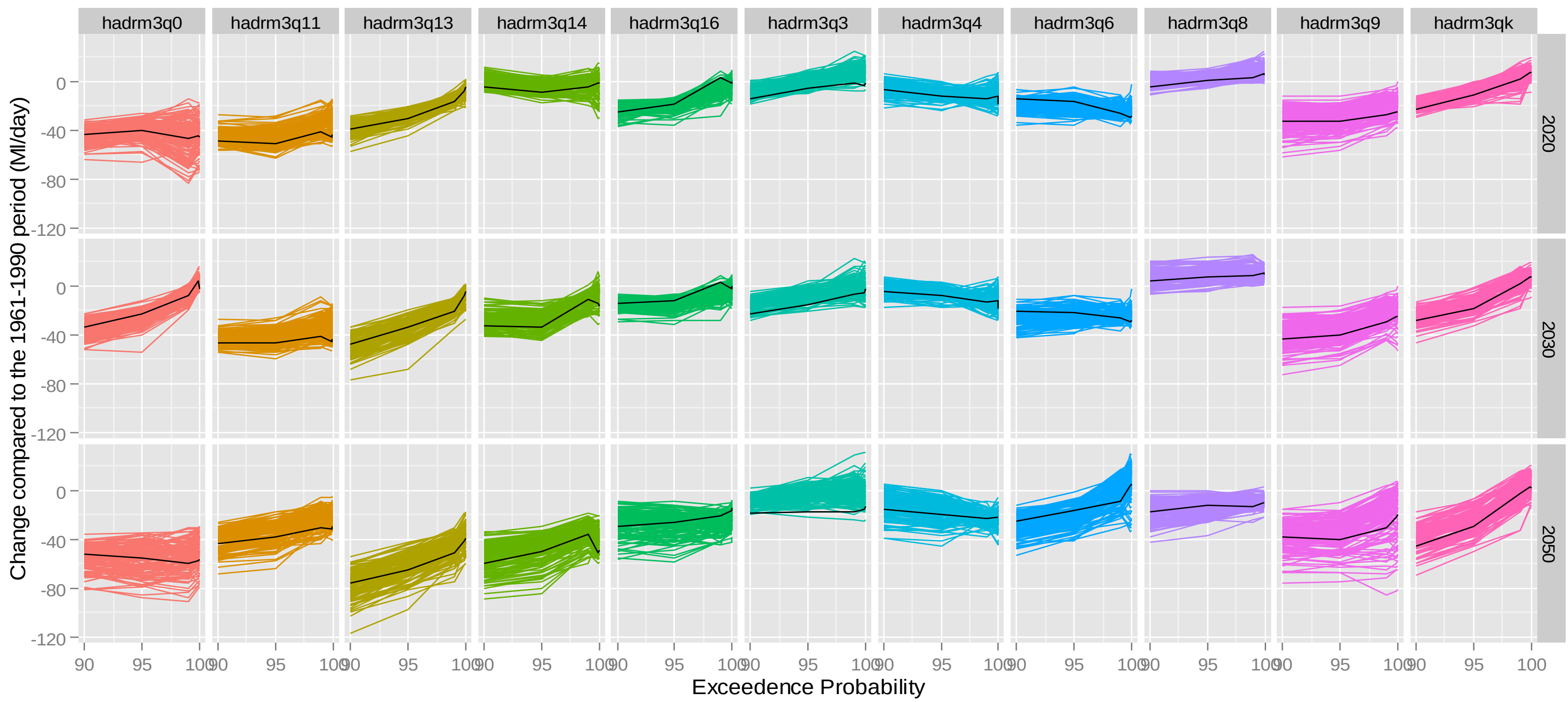


Figure 6.6 Changes of Q90, Q95, Q99 and Q99.99 compared to the 1961-1990 period in the RCM climate product Each line is one hydrological run out of the 131 behavioural CATCHMOD parameter sets.The black line shows the Nash 'optimal' parameter set of the GLUE ensemble, in order to compare the results of GLUE versus the classical calibration process.

This may be an artefact of the random sampling process, in which the sampling size is not sufficiently large to find a comprehensive sample of the behavioural parameter sets. Nevertheless, these hydrological outliers demonstrate a slightly different trend in low flow changes. As such, even if they belong to another behavioural group, they indicate that such behavioural group will also be different from the current group. Across the climate products, post-processing uncertainty is larger than the hydrological parameterisation uncertainty and the change of climate uncertainty over the time periods. Figure 6.7 and Figure 6.8 show that overall the changes in time are negligible compared to the difference amongst the climate product. For instance, the mean value of the RCM group in Q70 is consistently higher than that of the FF group. Yet, the range of RCM contains the range of FF and the range of SCP contains the range of UKCP09.

This suggests that using these products of larger bounds will lead to planning decisions that include the conditions projected in the FF and UKCP09 groups. In essence, using the 131 'behavioural' parameter sets, the CATCHMOD flow projections of the SCP and UKCP09 products systematically project higher flows than that of the RCM and FF products. Amongst the group, the error bounds of SCP, UKCP09 and FF are comparable, while that of RCM is significantly wider. Low flow analysis of all the products show negligible changes from 2020s to 2030s, and a slight flow reduction in 2050s. In Figure 6.8, all climate products show a mean flow reduction in 2050s and a slightly widening uncertainty bound in time. It also shows systematic bias in each climate product, which dominates the overall uncertainty. The uncertainty range indicated by each box plot consists of the equifinality uncertainty (due to using different parameterization) and climate projection uncertainty (due to using different realisations/projections within the product). The dominance of climate product uncertainty compared to the internal hydrological and climate uncertainty is important. It shows that there is a further need to cross validate and investigate the processing of these products, as they are all based on similar sources and sample different factors of uncertainty in the climate modelling process. Their significantly different flow projections imply that such uncertainty may further cascade down the modelling process and may lead to different adaptation and planning decision depending on which climate product is employed. To date, all of these products have been used in adaptation studies, with the SCP and UKCP09 being used for water resource plans in England and Wales, the RCM being used for several climate change research studies and the FF projections used to assess climate risks in key catchments.

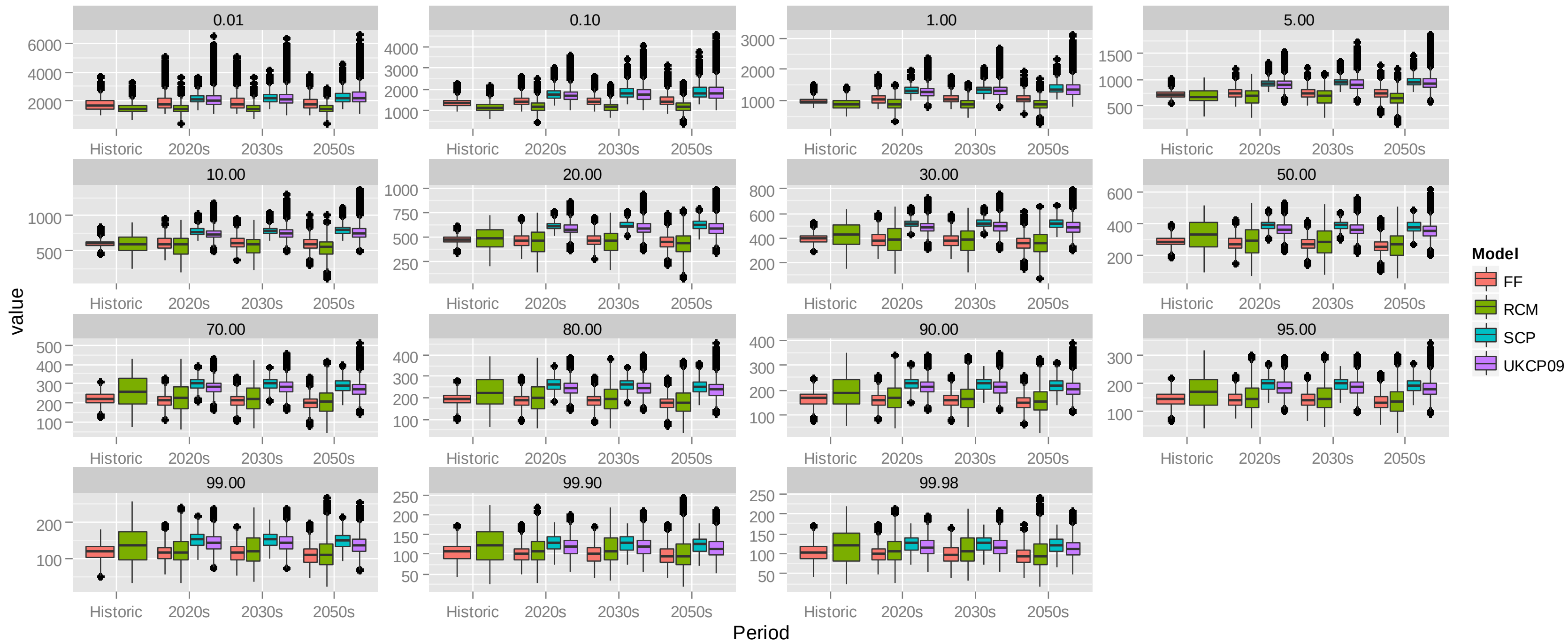


Figure 6.7 Box plots showing the changing trend of flow quantiles (Ml/day) from the historic period to 2020s, 2030s, and 2050s as projected by the four climate products. Note that for the historic period (1961-1990), the group consists of the 1961-1990 time series of the FF and the RCM product, as SCP and UKCP09 are based on the observed data.

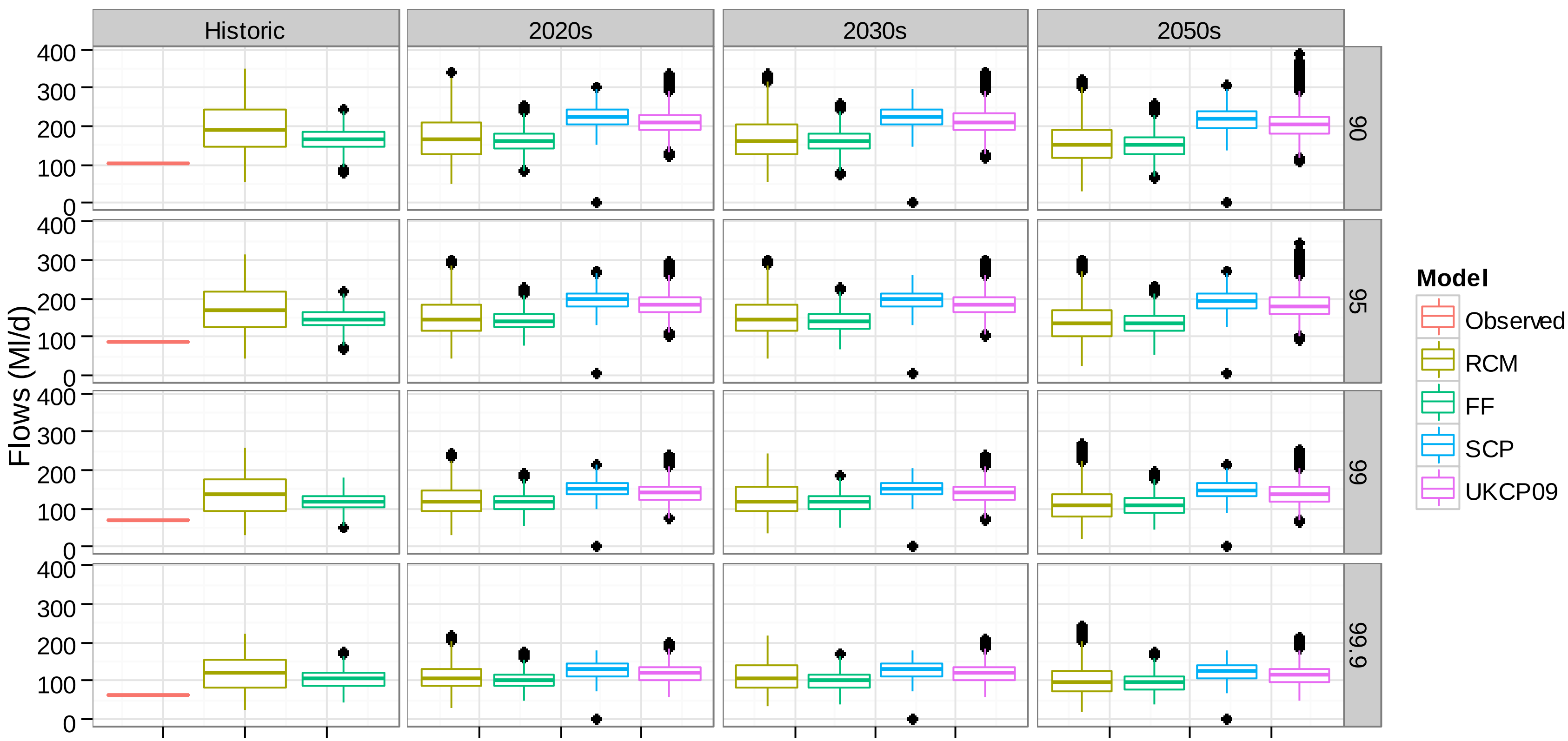


Figure 6.8 A closer look at the different projections in low flow quantiles with the additional data of the observed 1990-2005 flows for comparison.

6.3.3. Sobol analysis of parameter influences

Further to the GLUE analysis, a Sobol analysis was conducted. Due to time and computational constraints, the focus was on historic gridded data and the 1959-2069 time series of the Future Flow climate product. As the simulated FF flows are not supposed to be identical to the observed flows (Prudhomme et al., 2012), a comparison with historic observed data was not conducted; the aim was instead to identify parameter influences on the range of low flows and high flows.

6.3.3.1. Flow analysis of the 1959-2004 historic flows

Table 6-3 demonstrates the Sobol sensitivity indices of the most influential parameters or interactions on the corresponding criterion. The low flow criterion is assumed to be a proxy of the worst drought case of the simulation (which expands more than just the calibration period); this value is not related to the actual observation flows. Meanwhile the log Nash and Nash value are two indicators of the simulation goodness-of-fit to the observation values. The log Nash criterion tends to indicate the low-flow goodness-of-fit while Nash indicates the goodness-of-fit in the mid and high flows.

Table 6-3 Sobol sensitivity indices of the 10 most influential parameters or interactions on the corresponding criteria. The low flow criterion is the lowest total 7-day flows in the simulation (therefore not related to the observed flow). The Nash and log Nash represent how closely the simulation results to the observation of high and low magnitudes. The * symbol indicates the interaction between the two parameters. *The number after the name of each parameter indicates the contributing zone/catchment; for parameters such as Q1, the sub-catchment index will be separated by an underscore.*

Low flows			log Nash			Nash		
	mean	std. Error		mean	std. Error		mean	std. Error
Cq3	0.95	0.68	Cq2	0.29	0.19	Cq2	0.29	0.26

Cq1	0.86	0.96	Cq3	0.22	0.23	Phi2*Cq2	0.23	0.46
Cq2	0.86	0.92	Cq1	0.18	0.21	Phi1*Cq1	0.22	0.32
Cq6	0.74	0.93	Cq6	0.08	0.20	Cq3	0.14	0.41
Slope1	0.70	1.03	Phi1*Cq1	0.07	0.21	Cq1*Cq2	0.08	0.33
Pdc1	0.70	1.01	Phi6	0.06	0.20	Cq1*Cq3	0.07	0.35
Pdc6	0.69	1.03	Pdc3	0.05	0.19	Cq2*Cq6	0.07	0.35
Pdc3	0.69	0.96	Phi1	0.05	0.19	Phi2	0.07	0.32
Phi2	0.68	1.01	Phi2	0.04	0.20	Pdc6*Cq6	0.06	0.34
Cq5	0.67	1.00	Cq4	0.03	0.19	Slope6*Cq6	0.06	0.33

6.3.3.2.Low flow indicators

Analysis on the historic flows of 1959-2004 show that both the lowest total 7-day flows and the log Nash value are strongly controlled by the non-linear storage constant of the 1st, 2nd and the 3rd contributing zone, the three largest zones of the catchment (Figure 6.9 and Figure 9.10). The figures show a positive relation between Cq and 7-day low flows and a negative relation between Cq and log-Nash. Therefore, the higher Cq is, the wetter the simulation is. As the actual driest flow in the catchment tends toward the dry case of approximate 700-1000 Ml/week, small Cq values lead to a better low flow fit.

The dominance of Cq during the low flow periods can be explained by the soil function that the parameter represents: the base flow release rate. Low flows often occur in prolonged periods of limited rainfall and/or excessive evaporation. In such circumstances, the upper soil storage and the unsaturated zone are often dry and can contribute little to the underlying storages. This thus explains the limited role of the parameters representing those processes. On the contrary, base flow is a significant contributor to river flows when other sources wane. As the correlation analysis between SPEI and observed flows has shown, flows in the dry period are weakly dependent on the actual rainfall and PET balance of that month. During these periods, flows rely on soil storages, which were accumulated in the previous rainfall events. As such, a model with a larger value of Cq, implying a higher releasing rate, will contribute to higher flows. Furthermore, Cq is the releasing rate per km^2; consequently, the total release volume would be the product of the unit releasing rate and the area of the contributing zone. As such, sub catchment area and the value of Cq are two important factors deciding the overall flows. This influence is evident in

Figure **6.10**, in which low flows increase when the value of Cq increases, particularly in the large sub-catchment. The controlling role of Cq on log Nash value also indicates that this is an important parameter in calibrating low flows.

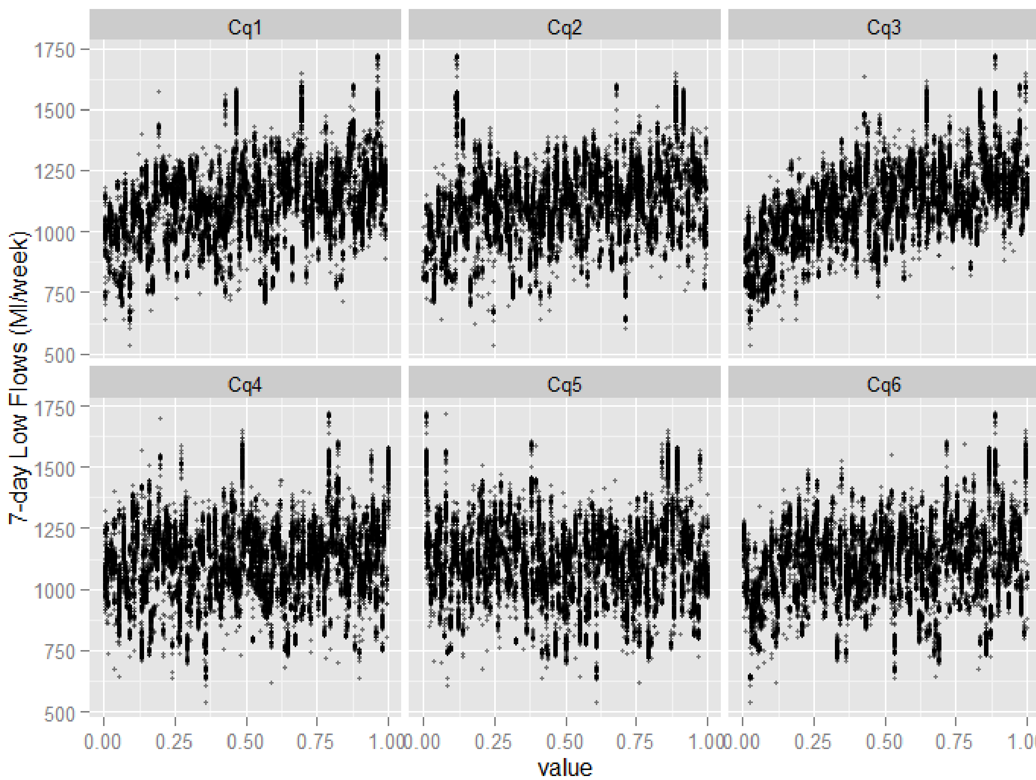


Figure 6.9 Graph of the standardized Cq versus the lowest total 7-day flows in six contributing zones. As can be seen, Cq3 shows a less noisy correlation between the low flows and the Cq3 value.

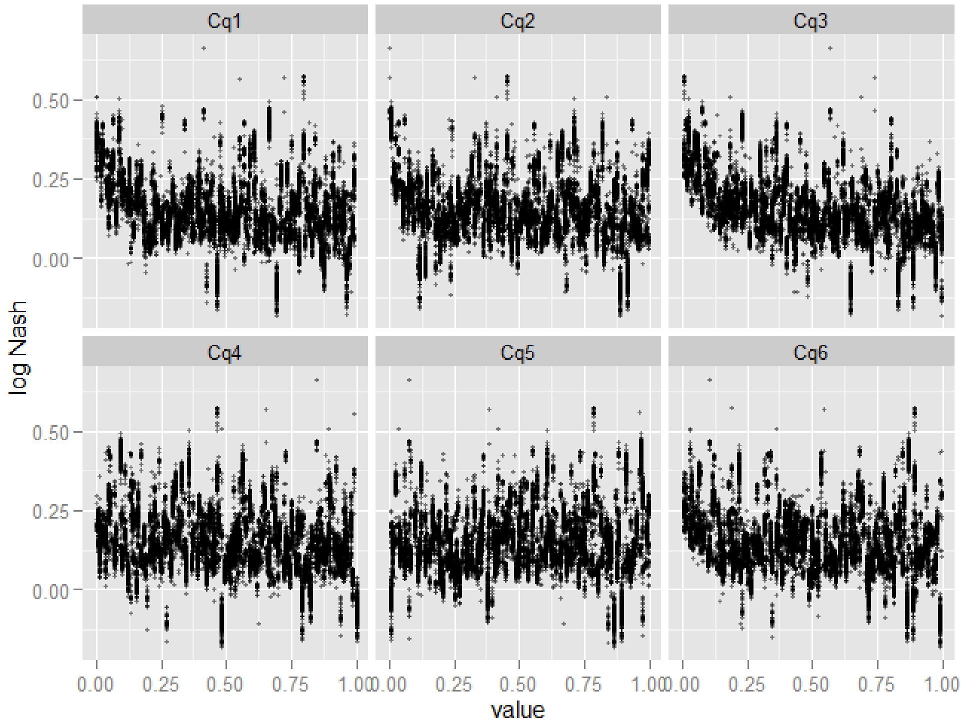


Figure 6.10 Graph of the standardized Cq versus the log Nash value. As can be seen, the signal is noisier than compared to the case of the low flow criterion. The Sobol indices also reflect this weaker correlation, with indices peak at 0.29 instead of 0.95 like in the previous case. The relation between Cq and log Nash is negative, with smaller Cq value seems to lead to a better fitted low-flow.

6.3.3.3.Nash value

The Nash value, as previously discussed, is indicative of model goodness-of-fit in high flows. According to the Sobol indices, the Nash values are controlled by Cq2 and the interactions between the linear and the non-linear storage in sub catchment 1 and 2. The influencing parameters also include parameters representing the soil moisture process such as Pdc (storage of the upper soil moisture storage) and Slope of the drying curve, which dictates how fast the soil dries out. The dominant role of Cq2 and Cq3, again, demonstrates that the Rother catchment is dominated by base flow, so that even in periods of high flows, the base flow still control the overall flows. However, the indices also reflect the more connecting interaction between the upper soil storage and the underlying storages in such wet periods. In essence, the influence of Cq2 and Phi2, the unsaturated zone that receives percolation from the soil moisture store and direct rainfall, shows the direct contribution of rainfall events. The analysis also implies the need to obtain both acceptable Phi and Cq values, as well as a well-fitted Cq values across the contributing zones in order to correctly reflect the catchment processes in high flows. Figure 6.11 shows that while the Cq2 and Phi2 interaction has a strong influence on the Nash criterion, that influence is not monotonous. As can be seen, there are pockets of local minima and maxima. This further affirms the need to conduct a global sampling on the parameter sets, since acceptable parameter combinations can exist in various place in the sampling space.

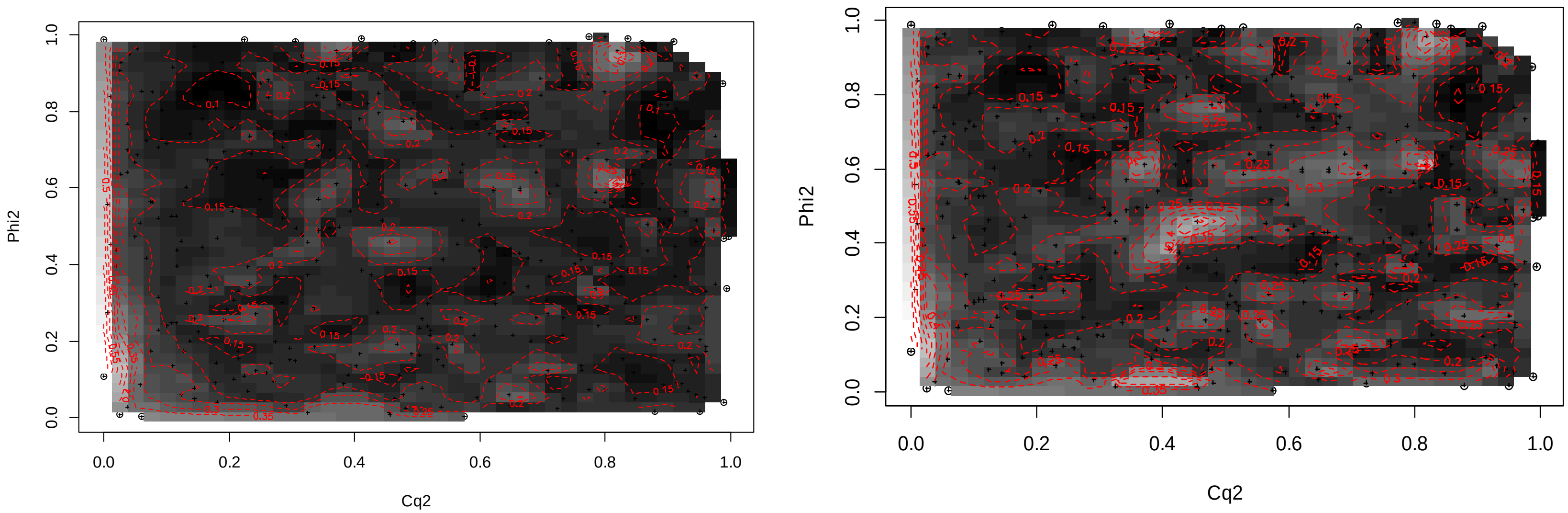


Figure 6.11 Contour plot of the influence of the interaction of Phi2 and Cq2 on the overall Nash value. Due to the experimental design, each pair of Phi2 and Cq2 contains several runs with same Phi2 and Cq2 values but with other parameters being varied. The first surface represents the mean Nash value of all those runs. The second surface represents the max value of all those runs. The black cross represents the actual parameter pairs. Overall, both the mean and max response surface of Phi2 and Cq2 are not monotonic to the Nash coefficient.

6.3.3.4.The influence of the initial conditions

Regarding the influence of the initial conditions on the simulation, Table 6-3 Sobol sensitivity indices of the 10 most influential parameters or interactions on the corresponding criteria. does not indicate any initial condition parameters as an influencing factor. Upon a close inspection of the whole parameter list, the initial condition parameter D1, Q1 and R1 appear to have certain influence on the 7-day low flows but not on the criteria of log Nash and Nash. This can be explained by the difference between the two groups of criteria. In the case of log Nash and Nash, regardless of the initial conditions, there likely exists a parameter set that can compensate the dryness or wetness of the initial conditions and slowly mitigate the effect. Furthermore, the calibration period is from 1990 to 2004, while the model starts from 1959. Over time, the effect of the initial conditions are likely to be dampened by the influence of other parameters; however if the calibration period has been closer to the starting time step, the influence of the initial conditions will grow. Meanwhile, the low flow period can occur in any time step of the simulation. Therefore, while the initial conditions are not the dominant factor, drier initial conditions once coupled with small catchment storage can lead to a lower 7-day flow than in the case of wetter initial conditions.

6.3.4. Future Flows analysis on parameter influences

6.3.4.1.Low flows

In the FF climate product, the non-linear storage constant Cq of catchment 1 and 3, the slope of drying curve of catchment 1 and the linear storage constant Pdc of the catchments are among the ten most influential factors on low flow simulation (Table 6-4).

Table 6-4 Sobol sensitivity indices of the 10 most influential CATCHMOD parameters or interactions on the low flow of the FF climate product. The low flow criterion is the lowest total 7-day flows in the simulation (therefore not related to the observed flow) not including the first simulation year. The * symbol indicates the interaction between the two parameters.

Historic		2020s		2030s		2050s	
Parameters	Average Sobol	Parameters	Average Sobol	Parameters	Average Sobol	Parameters	Average Sobol
Cq3	0.92	**Cq1**	0.78	**Cq1**	0.70	**Cq1**	0.60
Slope1	0.87	**Slope1**	0.77	**Cq3**	0.68	**Slope1**	0.60
Cq1	0.87	**Cq3**	0.75	**Slope1**	0.67	**Cq3**	0.59
Pdc1	0.78	**Pdc1**	0.67	**Pdc1**	0.60	**Pdc1**	0.48
Cq4	0.77	**Pdc6**	0.65	**Pdc6**	0.58	**Pdc3**	0.46
Pdc6	0.77	**Dp6**	0.64	**Pdc3**	0.57	**Pdc6**	0.46
Dp6	0.77	**Cq5**	0.63	**Dp6**	0.56	**Cq6**	0.46
Phi2	0.77	**Phi2**	0.62	**Phi2**	0.55	**Phi2**	0.45
Cq5	0.76	**Phi3**	0.62	**Cq5**	0.55	**Slope6**	0.44
Phi3	0.76	**Cq4**	0.62	**Phi3**	0.55	**Dp6**	0.44

Their ranking and sensitivity are subject to uncertainty, since the sensitivity indices were estimated based on the 200 samples. Yet, the dominance of parameters representing the lower storage zone demonstrates that under conditions projected by the FF climate product, base flow will still constitute a significant proportion in the river flows. Within the hydrological process, soil storage continues to play an important role in dictating flows in the dry period. There also exists a trend of declining Sobol sensitivity indices in these parameters. Such declining trend can either be the artefact of the sampling design, an indicator of the increasing importance of other parameters or due to the increasing influential role of rainfall and PET in restricting recharge. Since these are mean values of index estimation, there is not enough information for further assessment. Yet, this analysis indicates that recalibrating of these parameters and monitoring related changes in the corresponding catchment processes are needed to ensure that CATCHMOD parameterisation still reflects the catchment behaviour in such conditions.

6.3.4.2.High flows

Table 6-5 demonstrates the results of Sobol analysis on the highest weekly flows. The highest flow week appear to be related to the starting conditions (Q1 denotes the initial input of the non-linear storage and the number after the underscore symbol is the sub catchment number). The combined interaction of the upper and lower soil storage still appears to be influential in the catchment in the future, although it was not so in the FF simulated 1961-1990 period. Yet, as the Sobol indices of the high flows are much lower than those of the low flows, they are subject to even more uncertainty and therefore not provide sufficient evidence for the influence of the parameters. Nevertheless, it shows that the initial conditions still have certain effect on the simulation, despite the use of a 'warm-up' year.

Table 6-5 Sobol sensitivity indices of the 10 most influential CATCHMOD parameters or interactions on the high flows of the FF climate product. The high flow is the highest total 7-day flows in the simulation except for the first year. The * symbol indicates the interaction between the two parameters. *The number after the name of each parameter indicates the contributing zone/catchment; for parameters such as Q1, the sub-catchment index will be separated by an underscore.*

Historic		2020s		2030s		2050s	
Parameters	Average Sobol	Parameters	Average Sobol	Parameters	Average Sobol	Parameters	Average Sobol
Q1_3	0.41	**Q1_3**	0.32	**Q1_3**	0.31	**Q1_3**	0.29
Q1_2	0.34	**Q1_2**	0.26	**Q1_2**	0.25	**Q1_2**	0.22
Q1_5	0.27	**Q1_5**	0.16	**Cq3*Q1_6**	0.17	**Q1_4*Q1_5**	0.19
Q1_6	0.17	**Phi2*Cq2**	0.14	**Phi2*Cq2**	0.17	**Phi2*Cq2**	0.19
Q1_4	0.15	**Q1_4*Q1_5**	0.14	**Q1_4*Q1_5**	0.16	**Q1_4*Q1_6**	0.18
Q1_1	0.12	**Cq3*Q1_6**	0.13	**Q1_1*Q1_5**	0.16	**Cq3*Q1_6**	0.18

Cq1	0.09	**Q1_1*Q1_5**	0.13	**Q1_4*Q1_6**	0.15	**Q1_1*Q1_5**	0.18
Phi2	0.06	**Cq2*Q1_4**	0.12	**Q1_5*Q1_6**	0.15	**Q1_5*Q1_6**	0.17
Pdc2	0.06	**Q1_4*Q1_6**	0.12	**Cq2*Q1_4**	0.14	**Cq2*Q1_4**	0.17
Pdc3	0.05	**Q1_5*Q1_6**	0.11	**Q1_5**	0.13	**Cq1*Q1_5**	0.16

6.4.CONCLUSION

Overall, the chapter has assessed hydrological parameter uncertainty in relation to climate projections and climate product uncertainty discussed in Chapter 5. While several studies have shown that climate projection uncertainty is much larger than hydrological uncertainty, this study demonstrates that the uncertainty of using different climate products is even larger than the climate projection uncertainty. The analysis including equifinality hydrological uncertainty and climate projection uncertainty within different climate products shows a systematic bias amongst the flow projections of the products, in which RCM and FF consistently project lower flows than SCP and UKCP09 in all quantiles. The flow projections also show strong traces of climate inputs, in which the results of each climate product are relatively distinctive from those of others. As the hydrological parameter sets are the same for all products, these biases are likely to stem from the product itself. Yet, structural uncertainty is also a factor and as such, there is a need for future research to compare post-processing uncertainty and hydrological structural uncertainty.

Furthermore, the study shows a correlation between meteorological drought index and hydrological flows, and via that correlation, the buffering role of soil storage. In particular, hydrological droughts are less severe than the meteorological index indicates, as the soil storage can still release water from previous rainfall events and mitigate the dryness. Subsequently, SPEI based on a longer period appears to be more responsive to the actual flows. Various analysis of SPEI and parameter sensitivity analysis demonstrates that the catchment is dominated by base flows, in that the CATCHMOD parameter representing the base flow influences on both the low flow and high flow process. The Sobol sensitivity analysis of the historic data shows the dominant role of base flow not only in dry periods, when this is the main contribution of the river flows, but also in wetter periods when there are flows from the surface process and additional contribution of the upper storage. In the wetter period, the interaction of the connecting linear and non-linear storage also becomes important, as it represents the recharge from the storm. As such, in CATCHMOD hydrological modelling, the non-linear storage parameter Cq is important for model calibration in the low flow part and both Cq and Phi are important in the high flow part.

The Sobol analysis on the FF simulated flows of the 1961-1990, the 2020s, the 2030s and the 2050s periods shows that the base flow is still a controlling factor of low flows in the future. Meanwhile the Sobol indices of high flows project a much weaker influencing power of these parameters, but indicate that initial conditions can influence the high flows. While this specific observation needs more research and assessment for a comprehensive conclusion, it shows that there is a need to analyse the converging and diverging pattern of acceptable model parameterisation, as well as the importance of the starting conditions in hydrological modelling. The converging models in the calibration period may diverge if models are used outside their calibration conditions; this can become another uncertainty in the uncertainty cascade. Chapter 7 will continue the cascade of uncertainty from hydrological onto the water resource scale. Since post-processing uncertainty is still the dominant factor compared to hydrological uncertain and climate uncertainty, the focus will remain on this component, with the additional integration of water demand uncertainty and water resource model uncertainty.

Chapter 7. VULNERABILITY ANALYSIS USING WATER RESOURCE MODELS

7.1.INTRODUCTION

Under the pressure of population growth and climate change impacts, water resource vulnerability has manifested across scales and locations (Gan, 2000; Alcamo and Henrichs, 2002; Jain et al., 2002; Oki and Kanae, 2006). Vulnerability has been analysed using different indices to reflect the key aspects of the water system. At the global scale, Vörösmarty et al. (2000) has used the Water Balance Model (WBM) to show a pandemic increase of water scarcity under the 2020s projections of the Canadian Climate Centre general circulation model CGCM1 and Hadley Centre circulation model HadCM2. Vulnerability is represented by the ratio of water use/withdrawal to water discharge, with the 0.2-0.4 interval representing medium to high stress and the above-0.4 open interval representing severe stress. Similarly, Arnell (1999a) used the same index with an additional category of 0.1-0.2 representing low vulnerability of global water resources. Using these indices, he showed an increasing risk of global water stress from the 2020s to the 2030s under both HadCM2 and HadCM3 climate projections. Yet, the results for the 2050s were inconsistent between the two models: water stress would be reduced under the HadCM2 projections but increase under the HadCM3 projections (Arnell, 1999a). Other studies define vulnerability as the likely magnitude of failure, in essence followed the definition by Hashimoto et al. (1982b), to demonstrate the increasing vulnerability of water resources to droughts. Fowler et al. (2003) used the maximum supply-demand deficit as the criterion of failure to show that water resources in Yorkshire, England would likely be vulnerable to severe drought events by 2080. Lopez et al. (2009a), likewise, looked at the fraction of supply failures within two climate ensembles to analyse climate change impacts on water resource management in south west England.

Vulnerability analysis is vital in efficient adaptation, particularly under the deep uncertainty of climate change impacts. As briefly outlined in Chapter 1 and discussed in Chapter 3, vulnerability is a key concept in both the ‘top-down’ and ‘bottom-up’ approach in climate impact assessments. Its roles and definitions also highlight the ideological dichotomy between these approaches. To the ‘top-down’ cascade of climate impacts, vulnerability is the undesirable system states due to climate change impacts, and therefore is the end point of the assessment. On the contrary, ‘bottom-up’ vulnerability is the inherent system constraints that restrict climate adaptation, and subsequently the starting point of the assessment. Vulnerability is defined by Kelly and Adger (2000) as “the capacity of individuals and social groups to respond to, that is, to cope with, recover from or adapt to, any external stress”. As such, vulnerability is also closely aligned to the coping capacity and adaptation needs of a system. Yet, a final adaptation decision may also require trade-offs amongst vulnerability, reliability and resilience (Moy et al., 1986). Furthermore, such vulnerability and adaptation assessment should not stop at climate risks, as the final risks are influenced by other processes (Dessai et al., 2009), the decision context (Adger et al., 2007) and the modelling choices (Wilby, 2005). Even with accurate climate information, its cascade impacts on river flows and socio-economic responses will further generate deep uncertainty that requires robust decision making (Dessai et al., 2009).

The previous chapters have considered uncertainty from post-processing of the climate products and alternative parameterisation of hydrological models. This chapter continues that cascade of uncertainty onto the water resource scale. The main uncertainty component to be considered in this chapter is water resource model and demand uncertainty. In particular, hydrological flows from the different climate product are fed into two water resource models to analyse the vulnerability of the study area under alternative climate and socio-economic scenarios. The main aim of the chapter is to determine potential supply deficit in the study area if no adaptation is made. Section 7.2 will describe the methodology used in the vulnerability assessment, including the incorporation of the uncertainty factors and the water resource models. Section 7.3 presents the results and a discussion of the results. Section 7.4 then summarises the key vulnerabilities of the Sussex water resource system and the influence of the uncertainty factors on adaptation needs.

7.2.METHODOLOGY

7.2.1. The scenarios

As a methodology for decision making under deep uncertainty, a key attribute of robust decision making is vulnerability assessment under a wide range of scenarios (Groves et al., 2008; Lempert and Groves, 2010). Scenarios are highly useful to inform decision making under uncertainty since they could provide multiple descriptions of potential future conditions under a wide range of socio-economic and biophysical factors (Parson et al., 2007; Weaver et al., 2013). The scenario approach includes the normative scenario approaches (back casting), which explore the drivers to alternative future states, and the exploratory scenario approaches, which construct alternative plausible representations of the future to test robust strategies (Berkhout et al., 2002). The terminologies concerning scenarios in the study follow the exploratory approaches, in particular that of Downing et al. (2003), which defines scenarios as “plausible, internally consistent descriptions on possible futures”. Scenarios can further be categorised into main uncertainty or influencing factors, such as climate scenarios and socio-economic scenarios. Downing et al. (2003) also used “climate scenarios” for probable future climatic conditions and “socio-economic scenarios” for social, economic and political futures. The scenarios for this study combine climate uncertainty from four different climate products over the time periods of 2020s, 2030s and 2050s. Furthermore, the study considers other potential water demand changes due to the demographic and socio-economic trends. Therefore, the final scenarios considered in this study are integrated scenarios that consider risks from impacts of climate change and socio-economic shifts.

7.2.2. Climate scenarios

In this study, the climate scenarios use flow data from the four climate products described in Chapter 5. The flow data were generated from the hydrological model CATCHMOD using rainfall and PET inputs from the climate products. As Chapter 6 has demonstrated that hydrological uncertainty is much smaller than the uncertainty generated by different climate products, this chapter uses flow data from one set of CATCHMOD parameterisations. This parameterisation was used by Atkins Ltd. in the 2009 Water Resource Plan of Southern Water, the managing water company of the study area.

7.2.3. Socio-economic scenarios

Demand projection in the 2020s and the 2030s were based on Southern Water's projection for the 2009 Water Resource Management Plan. In this Plan, Southern Water extrapolates average and peak demand from 2009-2034, thus covering part of the 2020s and 2030s periods (Southern Water, 2009). The average dry year demand in 2024 and 2034 was selected to act as a representative demand for the 2020s and the 2030s, particularly during dry period. Demand projections were based on both historic data and projections provided by the water company and the Environment Agency for England and Wales.

Aside from these demographic-based projections, the Foresight Scenarios by the Environment Agency (Berkhout and Hertin, 2002; Science and Technology Policy Research, 2002) also provide a more general assessment of societal trend, including water demand, in the future. These scenarios describe alternative socio-economic states of the future society based on the spectrum of consumers and policy-makers choices

(Figure 7.1). The early Foresight scenarios (Berkhout and Hertin, 2002) were termed the World Markets, Global Responsibility, Local Stewardship and National Enterprise. These scenarios describe the influences of individualistic versus socially responsible behaviour (horizontal axis) and inter-connected versus locally autonomous governance (vertical axis). Within the Foresight 2020s, the Snapshot 2010 provided some estimates on GDP growth, economic activity and primary energy consumption. However, in these early scenarios, there was no direct reference to water demand and consumption.

Based on this initial scenario setting, the EA further published another report on levels and structure of water demand (Environment Agency, 2001). The Climate Change and Demand for Water (CCDEW) report (Downing et al., 2003) also used these Foresight Scenarios in combination with UKCP02 data to project water demand under different emission scenarios. The four original scenarios were then modified into the four demand scenarios: alpha, beta, gamma and delta, which correspond to Provincial (National) Enterprise, World Markets, Global Sustainability and Local Stewardship (Downing et al., 2003). These different socio-economic states will lead to different water consumption trends, with the per capita consumption jumping by approximate 1.5% during the transition from 2020s to 2050s under an alpha and beta Medium-High emission scenario and by 0.5% under a gamma/delta Medium-High emission scenario. This report also suggested that climate change impacts will increase agriculture and horticulture water demand by around 25-50%. These are significant rises, considering that water demand is also influenced by population growth and demographic changes. For the region of the study area, that impact lies from 23% in the 2020s Low Emission Scenario, 25% in the 2020s Medium-High Scenario to 42% and 49% increase in the 2050s Medium-High and the 2050s High Emission Scenario.

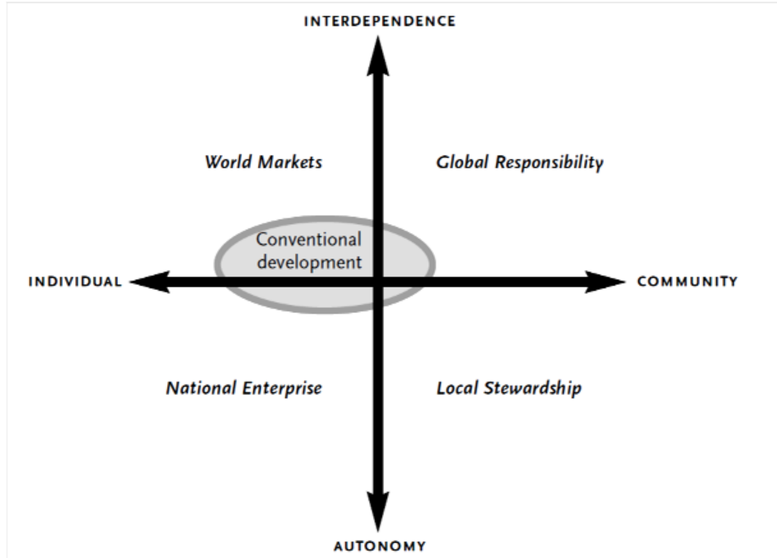


Figure 7.1 Four UK Future Scenarios for 2020s. Source: Science and Technology Policy Research (2002)

These storylines were further revisited and modified in the EA Scenarios for the 2030s and the 2050s. While the consumer attitude spectrum was slightly modified to reflect more closely the varying degrees of sustainability awareness, the governance axis was phrased explicitly into sustainability versus short-term socio-economic concerns instead of local versus globalised governance such as in the previous version. These scenarios, however, did not come with any assessment on water demand trends, all four scenarios share the same assumption of average per-capita water consumption of 153 l/d/capita and the different water consumption patterns in each scenario were described qualitatively. Figure 7.2 presents this version of the four 2030s Future Scenarios in a similar position to the 2020s scenarios. The 2030s scenarios appear to partially correlate to the SRES and the Foresight set (Burdett et al., 2006), in particular A1.-Jeopardy/Alchemy-World Markets; A2-Local Stewardship-Survivor; B1-Restoration/Alchemy-Global Sustainability; and B2-Local Stewardship-Survivor/Alchemy.

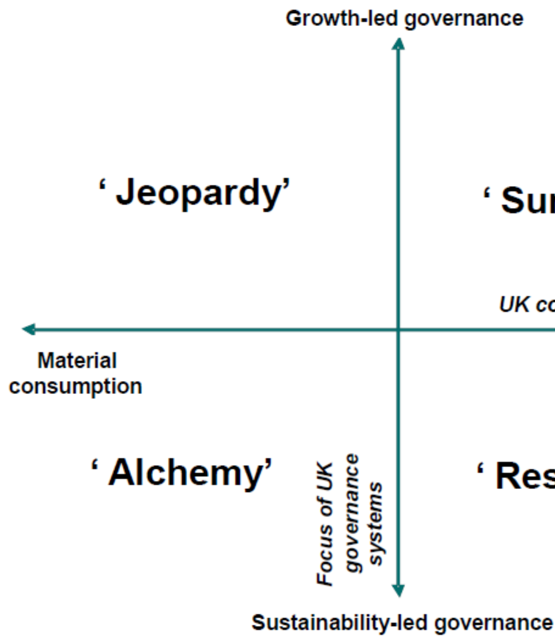


Figure 7.2 The 2030s four EA scenarios**. Source:** Burdett et al. (2006)

Finally, the newer Environment Agency projects demonstrate demand shifts for the 2050s under four scenarios, termed Sustainable Behaviour, Innovation, Local Resilience and Market Forces. Each of these scenarios reflects a different mode of governance and consumption (Environment Agency, 2008) (Figure 7.3). In essence, the projected change is as follows:

- **Innovation (I):** Total Demand reduces by 4%, water per capita consumption (pcc) 125 l/d/capita. The responsibility to find adaptation strategies lies with the government and scientist; demand reduction is due to sustainability-led governance and technological innovation.

- **Market Forces (MF):** Total Demand increases by 35%, pcc 165 l/d/capita. Water demand is driven by the market trend, focusing on cost optimisation and growth.

- **Local Resilience (LR):** Total Demand increases by 8%; pcc is 140 l/d/capita. People realise the need for demand reduction and take actions towards it. Their efforts, however, are moderate due to the low priority of demand saving and the lack of incentives from the government.

- **Sustainable Behaviour (SB):** Total Demand declines by 15% due to pro-active demand reduction from individuals; pcc is 110 l/d/capita.

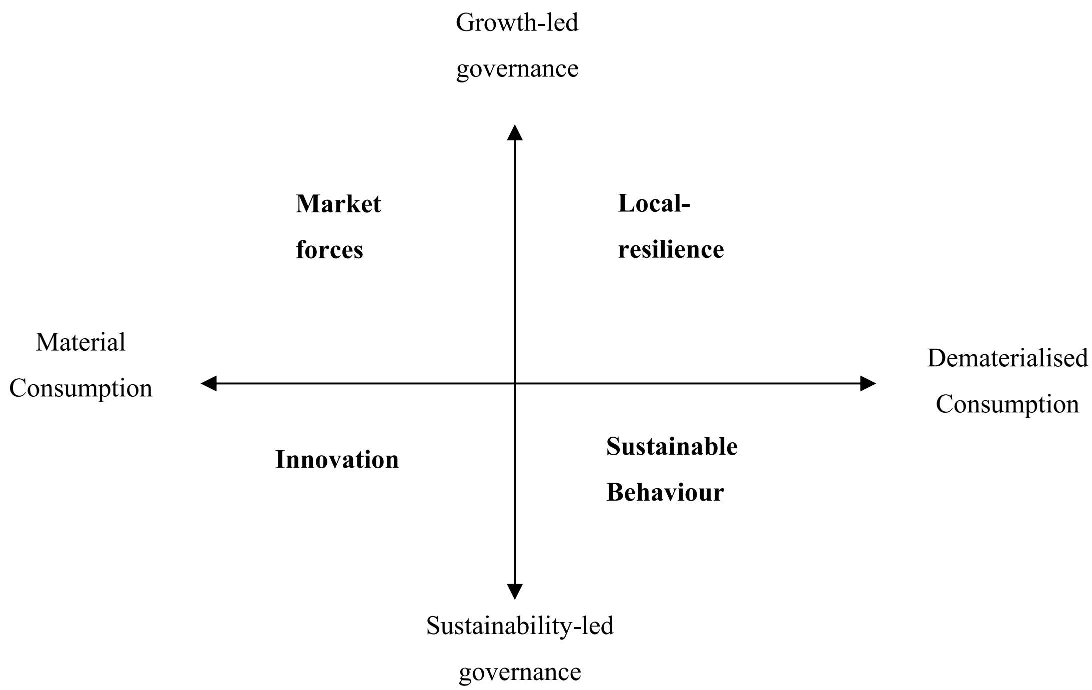


Figure 7.3 The four demand scenarios of the Environment Agency in England and Wales, modified after Environment Agency (2008)

Based on the EA 2050s projections, this study uses the projected annual demand by Southern Water to estimate the demand under the four 2050s socio-economic scenarios. Figure 7.4 depicts the baseline weekly demand profile and the headroom demand profile of the 2020s and Figure 7.5 shows the projections of mean weekly demand from the 2007 to the 2020s, the 2030s and different socio-economic scenarios of the 2050s. The projected annual demand in 2007-2034 was prepared by Southern Water based on several assumptions on future population growth, household number, metering proportion, metering effect and per capita water consumption. According to

Environment Agency (2008), the 2007 annual demand was used as a baseline to produce the four 2050s demand profiles under the corresponding socio-economic scenarios. In Southern Water resource management plan, the daily pattern of the demand profile was based on the estimated 1995 daily water demand. Water demand of subsequent years was linearly scaled by the ratio of the projected annual demand and the 1995 annual demand. Therefore, the same 1995 daily demand profile was linearly scaled to produce the 2020s, 2030s and four 2050s weekly demand profiles. For water supply, the peak season is often from late April to early September; on a weekly scale, this corresponds to week 17 to week 36. Water demand often rises within this period, as illustrated by Figure 7.4.

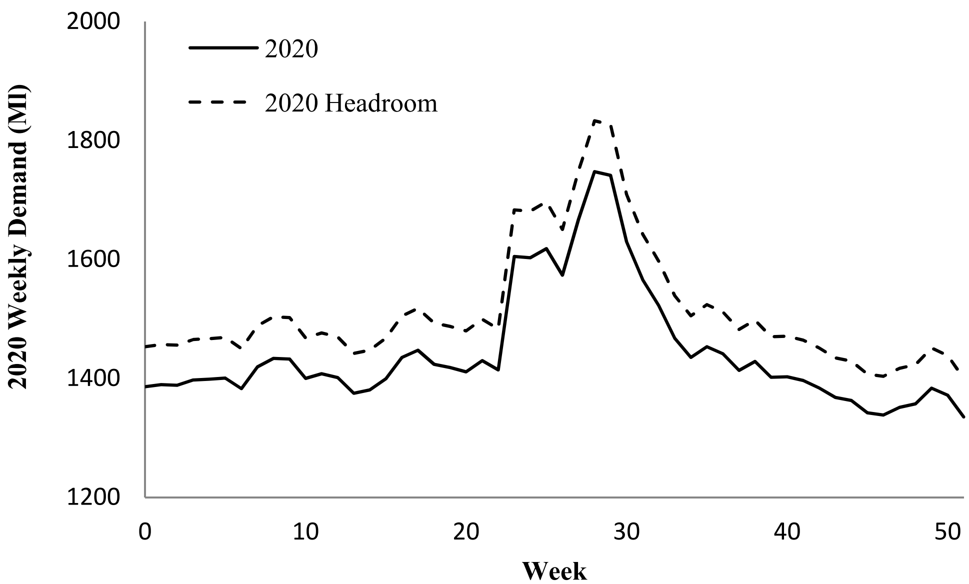


Figure 7.4 Weekly Demand Profile of Sussex water resource system in the 2020s based on 1995 demand data from Southern Water

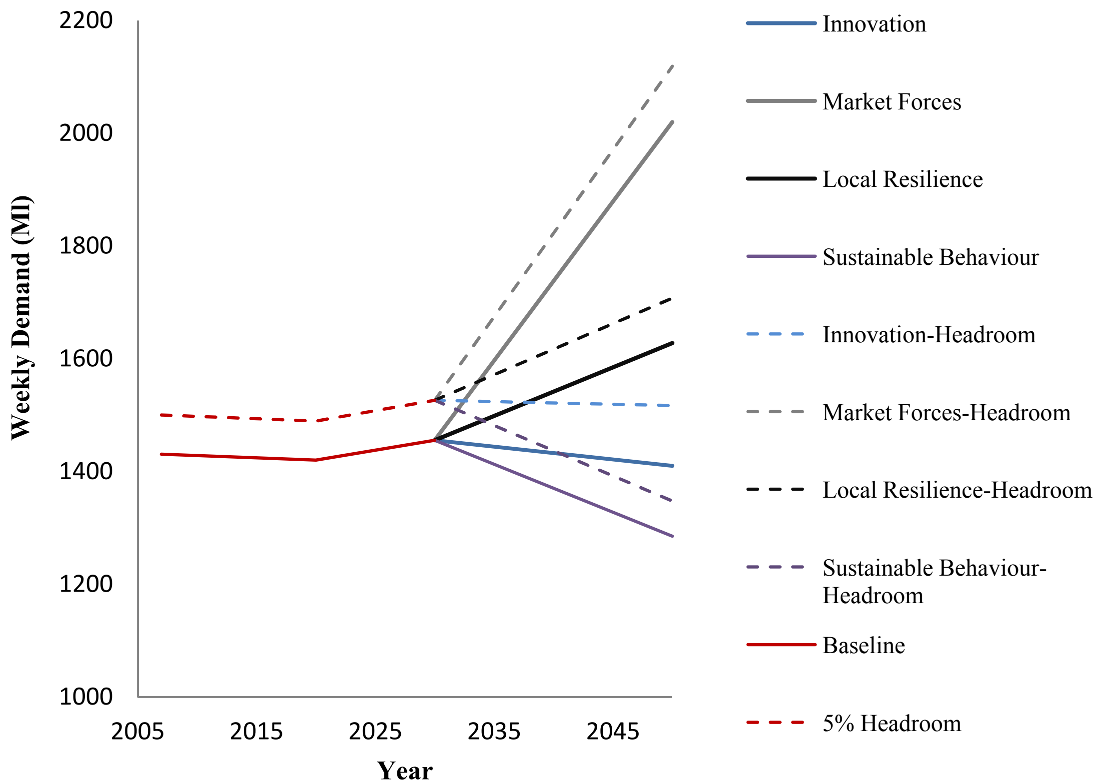


Figure 7.5 Weekly Demand of the Sussex water resource system from 2007 to 2050s

7.2.4. Water resource models

7.2.4.1. The reference model

The reference model in this study is the water resource model used by the water company and their planning consultancy. It uses Aquator, a water resource software application by Oxford Scientific Software Ltd. This model was constructed by Atkins Ltd. for Southern Water's Water Resource Management Plan 2009 and other forthcoming planning reports. The Aquator model represents the system in various demand and supply nodes, with the River Rother as a supply node and the Weirwood Reservoir as a reservoir node. Major supply sources include other groundwater nodes and a transfer agreement of 15 Ml/day from Portsmouth Water to Sussex North. The model displays the water planning system to a high resolution and has the transfer link from Sussex North to Sussex Worthing. In this model, Weirwood has to supply a fixed amount to South East Water before it can input water into other sources. Network analysis also shows that Weirwood can only input water into two nodes, the rest of the region being supplied by other sources. The demand profile used in the Aquator model was constructed by Atkins based on the same 1995 regional demand profile; water demand at individual nodes can vary slightly but overall sum up to the total regional demand profile on a daily scale. For a schematic of the model, please refer to Appendix A.

7.2.4.2.The VB.NET Simulation Model

This model was coded in VB.NET based on an Excel-based model by Wade (2005). Model parameters include the supply and demand capacity/profile of each node, the transfer capacity of each link, reservoir storage, reservoir operational curve and reservoir pumping capacity. The model consists of the River Rother, Weirwood, Hardham groundwater, other groundwater sources and transfer to and from other water companies (South East Water and Portsmouth Water). The model can use time series for groundwater sources and demand profile. All the demand nodes in each water resource zone were congregated into one to two regional demand nodes (Figure 7.6). These regional demands were constructed by summing the relevant individual demand profiles of the AQUATOR. Like the AQUATOR model, the groundwater nodes are subject to daily and annual licenses. This model simplifies the AQUATOR model to the scale of water resource zones, with each zone consisting of major proxy nodes instead of individual AQUATOR nodes. In particular, the Sussex North supply still includes the supply nods of Portsmouth, Hardham Groundwater, River Rother and Weirwood Reservoir. The link constraint representing the treatment capacity of the Hardham Water Supply Work (WSW) is included in the model; other transfer constrains within smaller demand nodes, however, does not present since these nodes have been aggregated into a single node. The supply from the Weirwood Reservoir is restricted by its pumping capacity of 21.8 Ml/day. Overall the demand for the Sussex North area is represented by the Sussex Demand node, the transfer agreement from Weirwood Reservoir is represented by the South East Water Transfer node. Similarly, the

Worthing and the Brighton area were constructed as single supply-single demand zones. For a brief description of the model, please refer to Appendix A.

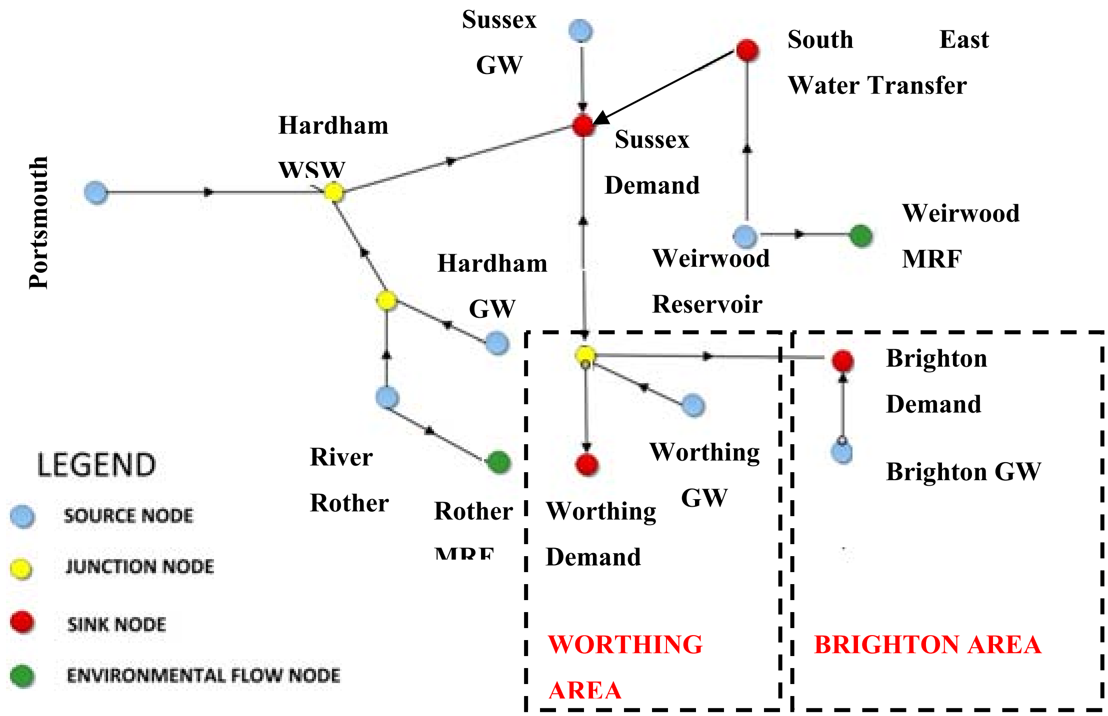


Figure 7.6 Schematic of the Sussex Simulation Model

7.2.4.3.The GAMS Optimisation Model

This model was coded in Generalised Algebraic Modelling Software (GAMS) based on a summary note on the Aquator model. The model simplifies the Aquator model but retains more details than the Simulation Model. Compared to the Simulation Model, the Optimisation Model has more detailed modelling of the water flows, including the transfer capacity in each link. The model can run in two modes: one based on the Aspiration–Reservation Based Decision Support (Makowski, 1994) and the hierarchical Ranked Optimisation (Rodrigues et al., 2002). The first one focuses on satisficing solutions that are within the acceptable zone of criteria values; the latter is sequential optimisation from the most important criteria to the least important criteria. After consultation with Southern Water, the decision makers indicated that they would be interested in the latter methodology since Southern Water has a clear hierarchy of criteria. In essence they have to comply with the environmental flow requirements and thus minimising the environmental deficit is the first priority. Then the system has to accommodate the water demand in Sussex. Finally amongst the candidate solutions that can minimise environmental and supply demand deficit, the third priority is to select one with the least cost.

As such, each scenario requires three model runs. For each scenario, the model first minimises total deficits in environmental flows; it then minimises the supply deficits while maintaining environmental deficit at that minimum level. Finally, for each Ml extracted from these sources, a corresponding cost will be added to the pumping cost (refer to Table 7-1). The model minimises the operational cost, which includes the pumping cost from sources and option-related capital and operation costs if any strategy is implemented. In this chapter, as there is no option implemented in the water system, the operational cost consists solely of the supplying cost.

Table 7-1 Supply cost of source nodes in the Sussex Optimisation Model

Source Nodes	Cost (£/ Ml)
Groundwater	50
HardhamGW	81
Portsmouth transfer	250
Rother River	45
Weirwood	80

These costs were based on model specification of the Aquator model, with slight alteration to reflect the supplying priority of the source nodes. As can be seen in Figure 7.7, compared to the Simulation Model, the Optimisation Model has a more detailed network configuration. In this model, the Sussex demand is represented by the nodes of

Upper Valley Demand, Sussex 2, Sussex 3, Turners Hill and Buchan Hill. In this model and the Aquator model, the Weirwood Reservoir can only supply for a part of the network instead of the whole Sussex Demand as in the Simulation Model. For model formulation and schematic, refer to Appendix A.

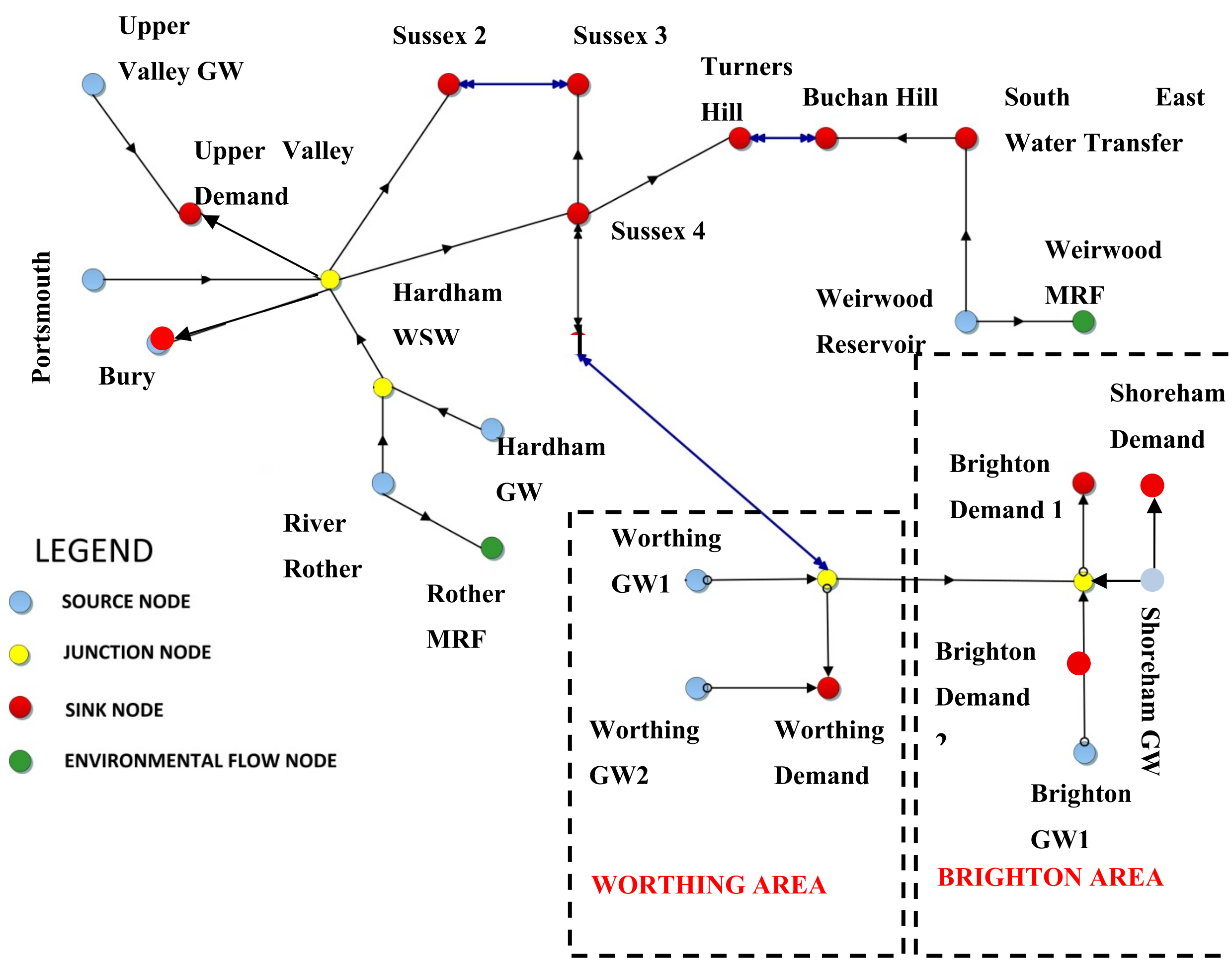


Figure 7.7 Schematic of the Sussex Optimisation Model

7.2.4.4.Comparison of the three models

Table 7-2 presents the main differences of the three models. The Aquator model is the most complex model but also has long run time. On the other hand, the simulation model and the optimisation model have shorter run time due to their simplified network version and less visual interface of the Aquator model. In this chapter, the vulnerability of the study area to droughts was analysed via the simulation and the optimisation models. The Aquator has a detailed network structure, with transferring constraints existing on many links, particularly in the Sussex Worthing and Sussex Brighton area. Meanwhile, the optimisation model and the simulation model implement transferring constraints at the regional level, such as on the link between Sussex North and Sussex Worthing. Additionally, the optimisation retains more details of the Sussex North and Sussex Brighton than the simulation model. Yet, the optimisation model runs on a weekly time step while the AQUATOR model and the simulation model use a daily time step. Model uncertainty due to different model structures and algorithms was analysed using an 1888-2005 reference input data. The input data for the future climate contain the full set (11 members) RCM, FF and SCP and a sampled set of UKCP09 (100 for the optimisation model and 1000 for the simulation model) in each time period 2020s, 2030s and 2050s.

Table 7-2 Comparison of the three water resource models

	Aquator	**Simulation Model**	**Optimisation Model**
Software description	i) Commercial software used by water companies and other consultancy companies in water resource planning; modelled by Atkins Ltd. ii) Has a Guided User Interface (GUI)	i)VB.NET program coded by Lan Hoang based on Wade (2009) ii) Has a simple GUI, very little visualisation	i) GAMS program coded by Lan Hoang based on the Aquator Sussex model ii) Can be used for other model network by changing input files iii) No GUI, linked to a Python visualisation tool
Timescale	Daily	Daily	Weekly
Spatial scale	Include North Sussex, Sussex Worthing and Sussex Brighton	Include North Sussex, Sussex Worthing and Sussex Brighton	Include North Sussex, Sussex Worthing and Sussex Brighton
Spatial Resolution	Individual supply and demand nodes within each region	Regional demands	Simplified nodes from Aquator network
Calculation Mode	Optimisation/Simulation	Simulation	Optimisation
Annual Groundwater Licenses	Yes-individual nodes	Yes-regional nodes	Yes-regional nodes but finer scale than those of the Simulation Model
Reservoir Control Curve	Yes-partially implemented	No	Year- can be partially or fully implemented

Demand Profile	Modified 1995 Regional Demand Profile downscaled to the node level	Modified 1995 Regional Demand Profile at the water resource zone level	Modified 1995 Regional Demand Profile at the sub-water resource zone level
Running time	~30 minutes per run	~15s per run	~2 minutes per run

7.3.RESULTS AND DISCUSSION

7.3.1. Comparison of the simulation and the optimisation model against the reference model

This section compares the performance of the two models based on the Aquator simulation of the Weirwood Reservoir from 1888-2005. The simulation model performs reasonably well compared to the original Aquator model (using Weirwood as an indicator). Spearman coefficient of Weirwood storage between the updated model and Aquator is 0.89; Pearson coefficient is 0.84 (see Figure 7.8).

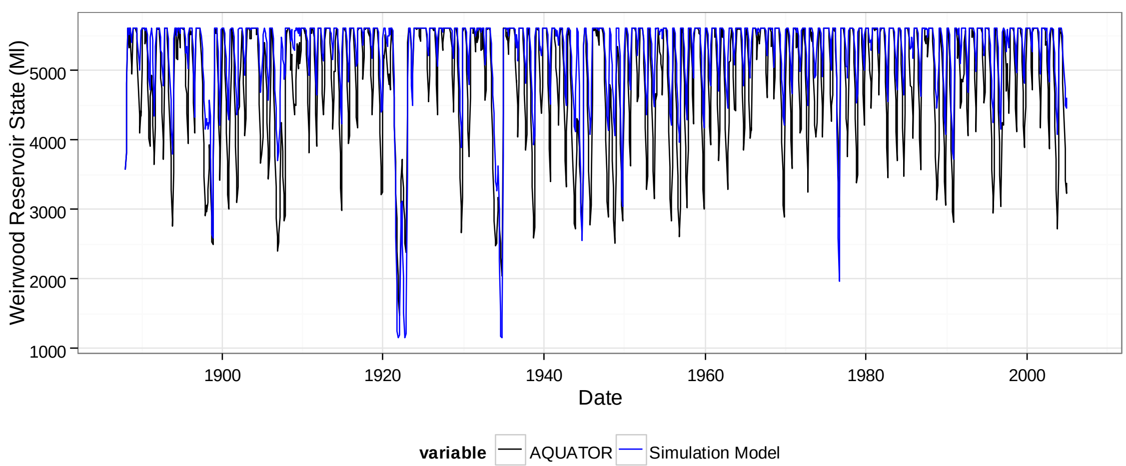


Figure 7.8 Simulated Weirwood reservoir state from 1888 to 2005

Both Aquator and the simulation model could reproduce the low reservoir state of the 1921/1922 and the 1975/1976 droughts, the two most serious events in the study area. For other less severe events, the simulation model tends to empty the reservoir less than the Aquator model. This feature is maybe due to the network resolution of the two models: Aquator has more transfer constraints and may have to rely on Weirwood to supply the Buchan Hill and Turner Hill nodes; meanwhile, the simulation model omits some link capacity hence in many cases can draw water from constrained River Rother and groundwater nodes to support these demand nodes. Overall, the simulation model indicated that the 1921/1922 drought was the most extreme event of the 1888-2005 time series and the 1975/1976 drought was the most severe event of the 1961-1990 sequence.

Meanwhile, the optimisation model-under a no reservoir control limit mode-shows more utilization of Weirwood Reservoir than the Aquator model (Figure 7.9). While the reservoir was emptied to the dead storage capacity only once in Aquator (during the 1921/1922 drought), Weirwood was emptied much more frequently for other minor droughts in the optimisation model. This is because the optimisation model optimises the reservoir state based on the whole 1888-2005 sequence, and thus in many cases does not use all the available inflows to fill the reservoir. It instead only route sufficient inflows to supply other nodes during the whole time period. Meanwhile, the Aquator model tends to fill the reservoir back to its capacity using all available inflows.

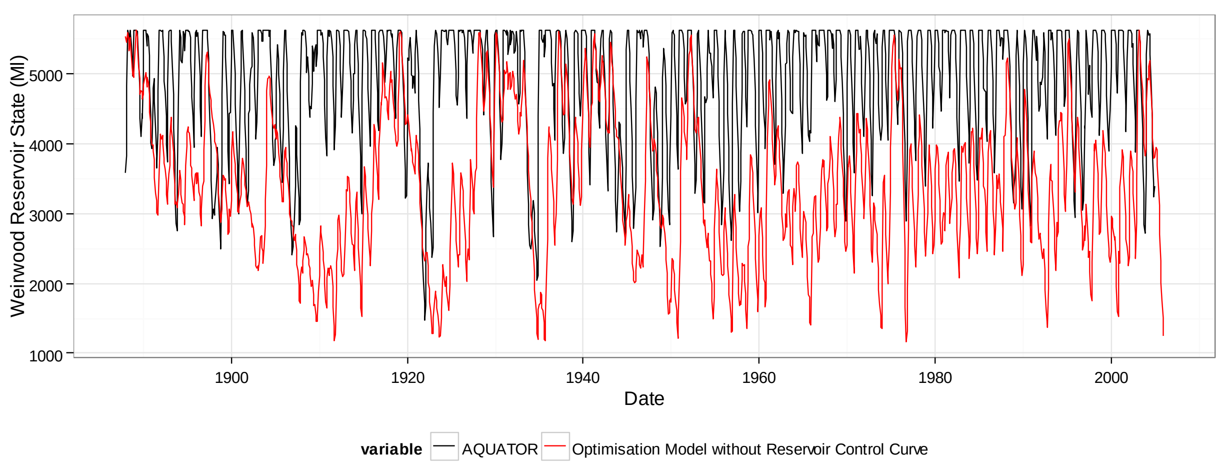


Figure 7.9 Comparison plot of Aquator versus the Optimisation model without Weirwood Reservoir Control Curve

The model specification note of the Aquator model stated that this model uses a Reservoir Control Curve-a monthly limit on the lowest possible reservoir storage. This is termed the Assess Management Plan 4 (corresponding to the 2009 Water Resource Plan) Control Curve, as the new Drought Plan has specified other trigger curves- not to control the actual level of the reservoir but as a drought trigger. The model, however, does not directly implement this condition. It instead mimics hosepipe bans, which reduce water demand, every time the Rother flows are below the 90th percentile of the Rother curve (the mean daily flows during the 1961-1990 period), therefore reduces demand pressure on Weirwood. The Optimisation model meanwhile can directly state the minimum allowed level of the reservoir, and thus maintain the level above the control curve (Figure 7.10). It can be seen that under this condition, the model does not allow emptying of the reservoir, even in the severe situations of the 1921/1922 and the 1975/1976 droughts.

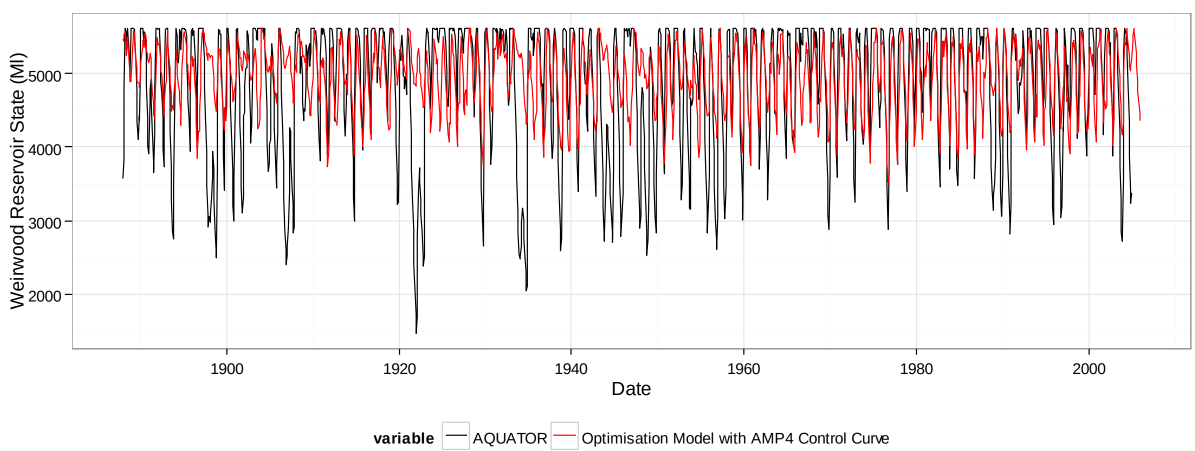


Figure 7.10 Aquator versus the Optimisation Model with an all-time implementation of the control curve

Comparing the minimum stage of Weirwood reservoir with the stated Aquator control curve shows that reservoir stage does fall below the control curve level (Figure 7.11).

This indicates that the control curve was not implemented or lifted in certain flow conditions.

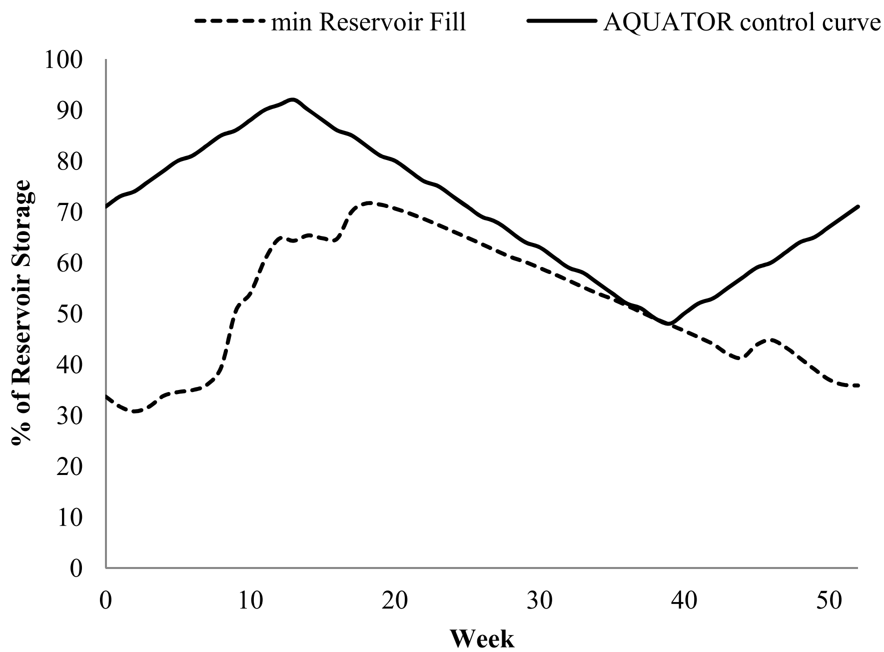


Figure 7.11 Comparison of the stated Aquator AMP4 control curve versus the actual minimum reservoir state in the run

However, if the control curve is only applied during the Rother flows are higher than the Recession curve, the Weirwood time series of the optimisation model become much closer to those of the Aquator model, in particular during the 1921/1922 drought. The optimisation model still exhibits a slight tendency to not take the full inflows; however this tendency is much less prominent compared to the previous cases (Figure 7.12).

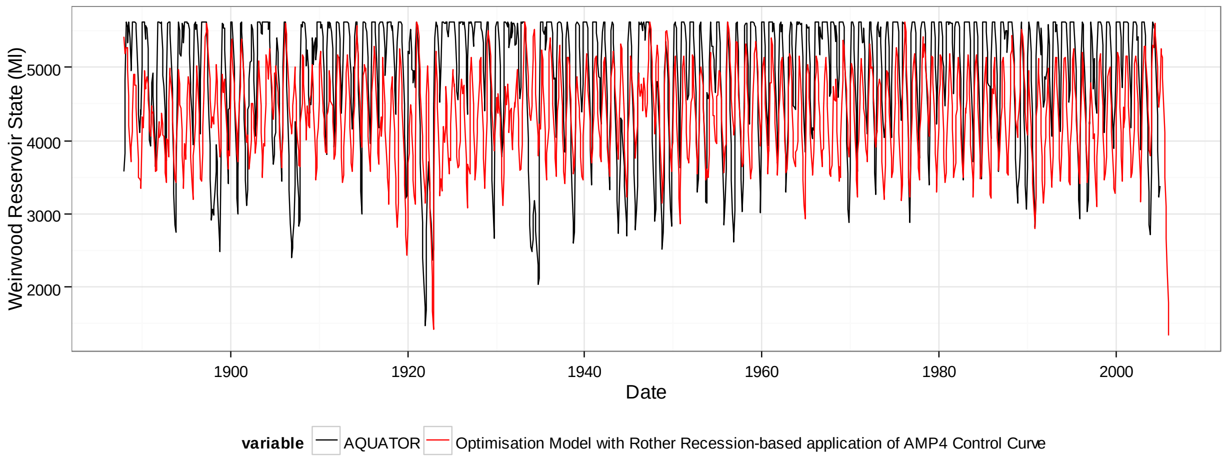


Figure 7.12 Comparison of Aquator versus the optimisation model if the control curve is only applied during high flows

Overall, the three models show structural uncertainty by using different algorithms and optimisation/simulation mode. These differences can contribute to the different supply deficit in each model (Table 7-3). A contributing factor is the network specification of each model, as Aquator is constrained on transfer capacity and has to rely on Weirwood in certain nodes; meanwhile, the simulation model and the optimisation model have a more relaxed constraint and therefore can be less dependent on Weirwood. The application of the control curve in each model also creates a slight discrepancy. Nevertheless, the control curve was left in the optimisation model as planning was done in prescriptive mode and the control curve would help preserve reservoir storage.

Table 7-3 Contributing factors to the reduction and increase of supply deficit in each model

	Simulation Model	Optimisation Model
Factors reducing deficits	Assumption of total system connectivity No reservoir control curve so can empty out reservoir to abate supply deficits	Optimisation mode Reservoir storage and annual groundwater licenses can be optimised with regard to the inflows and demand time series

		Coarse time step
Factors increasing deficits	Simulation mode	Constraints on link capacity
	Daily time step-can be subject to severe shortage at a daily time scale	Reservoir control curve can prevent water release

The optimisation and the simulation model were then used to further analyse the vulnerability under changing climate and water demand, according to the four climate products. The Aquator model was not used due to its time and computational requirements. Results from the optimisation and the simulation model were then compared to indicate any possible structure uncertainty and the range of climate and demand risks to the study area.

7.3.2. Simulation model results

The simulation model confirms that the water system is sensitive to drought conditions of the 1975-1976 and 1921-1922. If tested against the whole time series from 1888-2005, the drought period that brought the worst supply deficit were the 1921-1922 period. Otherwise, for a shortened time series of 1961 onwards, the 1975-1976 was the most serious drought. Model results using the four climate products again confirm the high level of uncertainty on possible impacts (Figure 7.13). In essence, the RCM and FF time series pose a higher risk of supply deficit than the SCP and the UKCP09 groups. While being significantly drier than the FF group in terms of rainfall (refer to Chapter 5), the RCM time series create a similar risk level to FF. The UKCP09 product, due to its wide range Bayesian probabilistic scenarios, projects a wide range of possible deficit prospects but not to the risk level of the FF and the RCM groups.

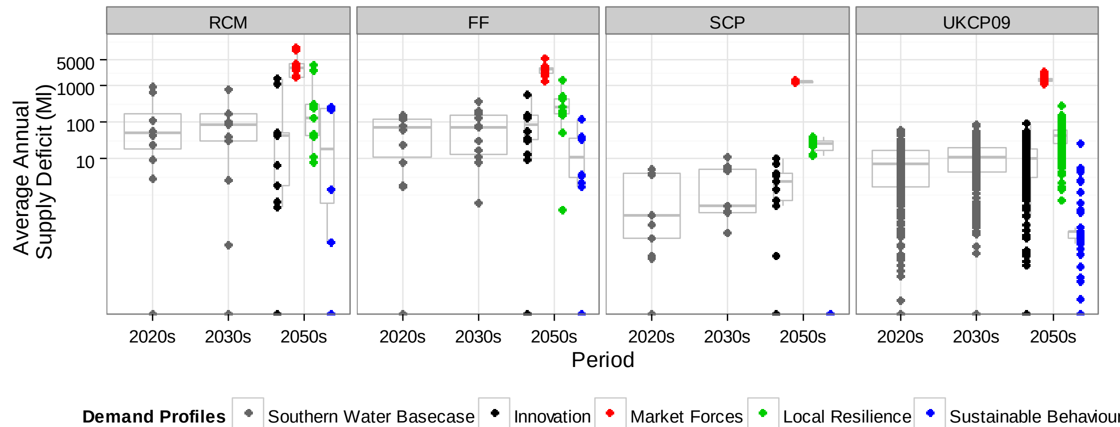


Figure 7.13 Average annual supply deficit in Sussex North, Sussex Worthing and Sussex Brighton in the 2020s, 2030s and the 2050s time period according to different climate products. The dots represent the deficit in each ensemble member/scenario of each climate product. The box plots at the background were provided for reference of the median and other statistics.

The alternative demand profiles representing different societal states, however, produce uncertainty of similar magnitude to climate post-processing uncertainty. Amongst these demand scenarios, only the most sustainability-oriented scenario could lower supply deficit from the 2020s/2030s level. The sustainability-led governance and individualistic consumption, Innovation, meanwhile appears to be a neutral scenario compared to the 2020s and 2030s period. Without sustainability-oriented governance, even if each individual exhibits environmental awareness and behaves responsibly, the water system still becomes less sustainable due to the overall demand increases (the Local Resilience scenario). Finally, the most extreme scenario in which both individual consumers and policy makers do not care for sustainability poses a significantly high risk of system failures. In this socio-demographic scenario, even under the mildest climate change prospect (projected by the SCP group), the system will experience high supply deficit. Once the society is at the Market Forces state, climate impacts appear to be much less influential compared to the demand impacts (which is a 35% demand increase from the 2007 baseline). This threshold of demand increase therefore is likely to represent a demand failing threshold of the system, in which the current Sussex system fails regardless of the supplying capacity.

Figure 7.14 further shows the spread in failure frequency (how many days of failure occurrence) and time span along the time periods (the number of years in which failure occurs- such as a scenario may have 200 failures concentrating in one severe drought year but another scenario may have 200 failures spreading over 10 years). Note that the points are frequently overlapped. Each point in this graph represents a member of the climate product, such as a run in the RCM ensembles or a scenario of the UKCP09 group. Overall the RCM group demonstrates high risks of failure that spreads over the whole 30-year time period. The graph also shows a structural difference in risk projection between the time series projection-based RCM/FF group and the modified-observation based SCP and UKCP09. In particular, the RCM and FF group project future time series that are unlike the observed 1961-1990 sequence; meanwhile, the UKCP09 and the SCP used the Change Factor method (refer to Chapter 5) to produce future projections from the observed 1961-1990. The drought type contained in the UKCP09 and SCP group is therefore modified drought risks of the Baseline period, in which the 1976 was the most significant drought. The results as such indicate that the water system was well insured against the 1976-drought type, which was probably due to the current practice of using the worst historic drought as the design event in water resource and drought planning. Yet, the results also indicate that the system is not immune to deficit risks due to demand growth, specifically under the Market Forces scenario. Again, if demand jumps by 25% from the 2007 level, supply deficit will be ubiquitous in the 2050s, presenting in every single year of the time series at a 60% daily occurrence risk level.

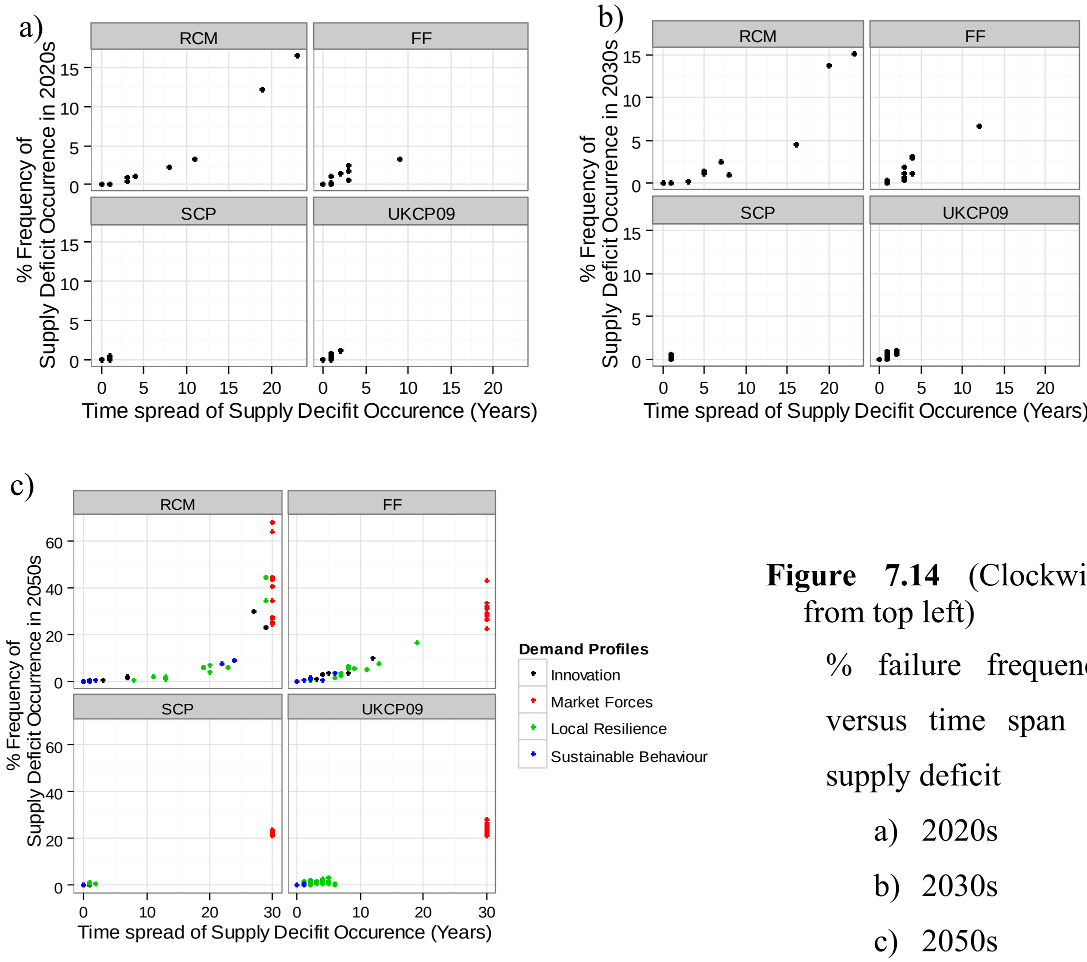


Figure 7.14 (Clockwise from top left)

% failure frequency versus time span of supply deficit

a) 2020s

b) 2030s

c) 2050s

7.3.3. Optimisation Model Results

Similar to the simulation model, the optimisation model demonstrates deep uncertainty of climate products and the socio-demographic scenarios, in that water supply deficits vary across the climate scenarios and climate products (Figure 7.15). Since the optimisation model could change reservoir supply and groundwater abstractions based on the different levels of water demand, the impacts of different demand uncertainty from the socio-economic scenarios are less noticeable than in the case of the simulation model. Aside from the Market Forces scenario, the Local Resilience scenario still poses a slightly higher deficit risk compared to the Innovation and the Sustainable Behaviour scenarios. The optimisation mode also shows that optimal operation based on the available supply can alleviate supply deficit. In practice, this is not achievable since such operation requires perfect information and prior knowledge of the future climate conditions. Nevertheless, the Market Forces scenario is still the failure threshold of the system, in which the system fails in every 2050s climate conditions. In terms of environmental flows in the River Rother (Figure 7.16a), except for the RCM group, the river flows may frequently fall below the current minimum environmental flows, reflecting drier river states and the reducing supply capacity of the Rother to the Sussex water supply system. The supplying cost (Figure 7.16b) is mainly driven by the supply cost of sources; despite the slight variation in cost of alternative sources, the overall cost is mostly influenced by the water demand level and remains relatively stable across the climate products.

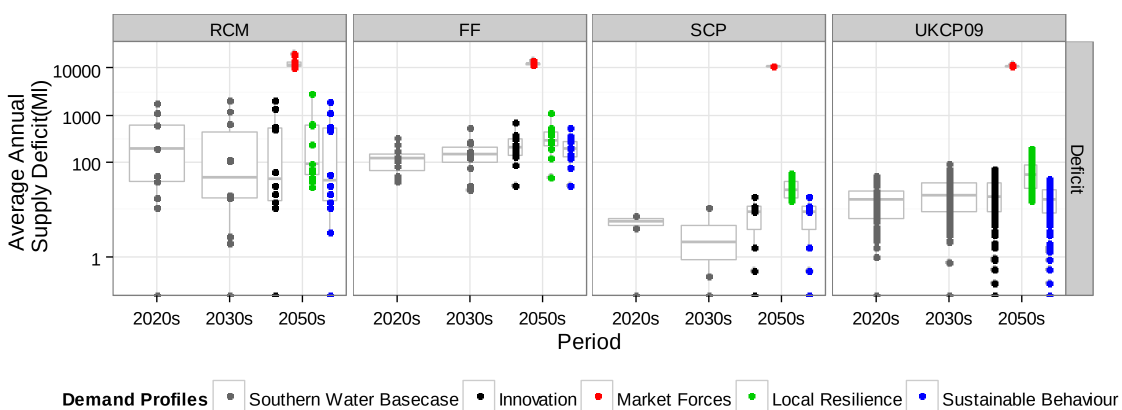
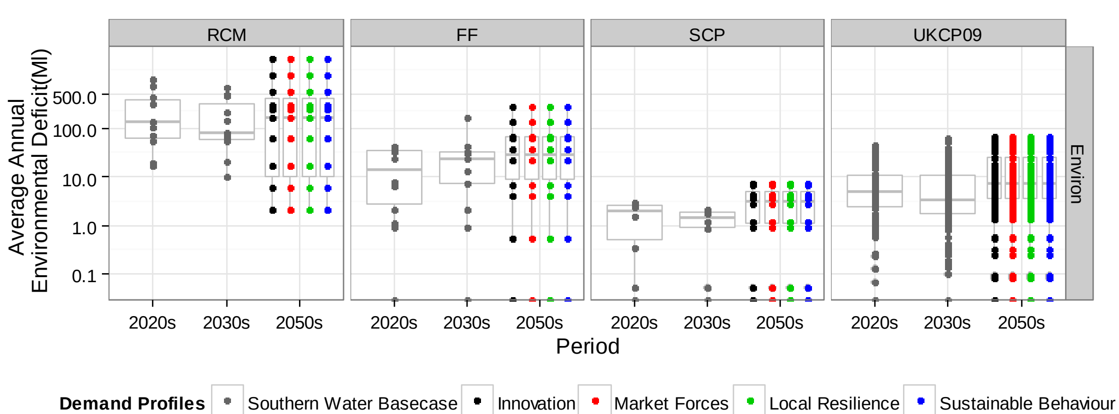


Figure 7.15 Sussex supply deficit over time periods

a)



b)

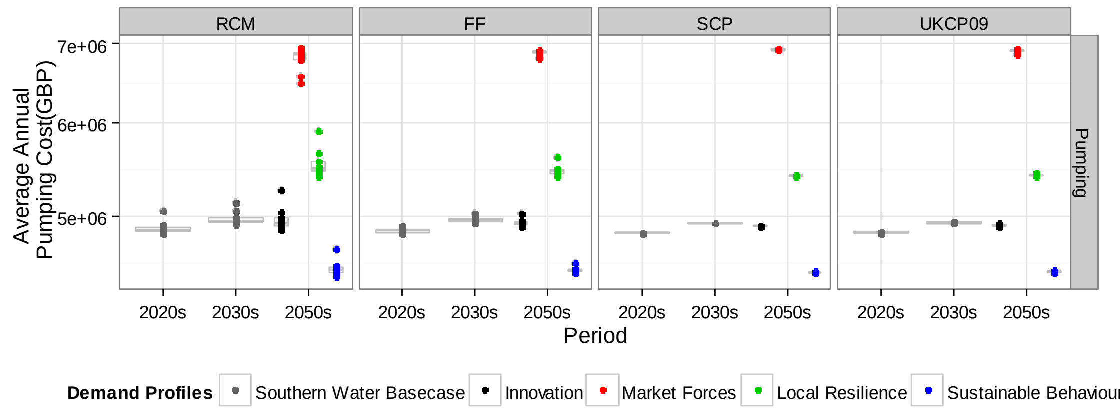


Figure 7.16 Sussex environmental deficits (7.16a) and pumping cost (7.16b) over time periods

7.3.4. Vulnerable areas

This section analyses the particular location of deficit occurrence according to the optimisation model. The simulation model only represents demand nodes at the resource zone level and therefore cannot indicate the specific location of the deficit. Overall, within the 2020s and the 2030s, deficit only occurs in the Sussex North area (Figure 7.17 and Figure 7.18). Asides from the inter-company transfer to South East Water and the environmental flow deficits in Rother and Weirwood, deficit in other nodes appear to be negligible. The graphs also show the heterogeneous distribution of risks on the network according to the different climate products. Overall, RCM and FF climate conditions will lead to more severe deficits while the SCP group rarely leads to any deficit or system failures. However, in Buchant Hills, Sussex2 and Sussex 3, the risks across the climate product are similar, while in Bury, the risk by RCM conditions is higher than the FF and UKCP09 conditions. Furthermore, while the RCM and the FF group only contain 11 ensemble members while the UKCP09 sample contain 100 members, the RCM and the FF group project a wide range of deficit impacts that is comparable to that of the UKCP09 group.

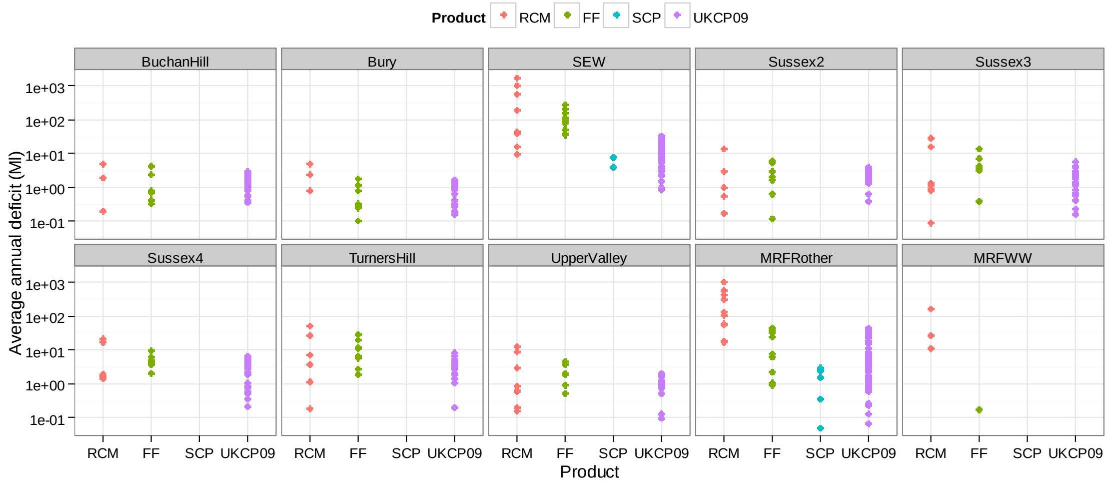


Figure 7.17 Deficit locations in the 2020s

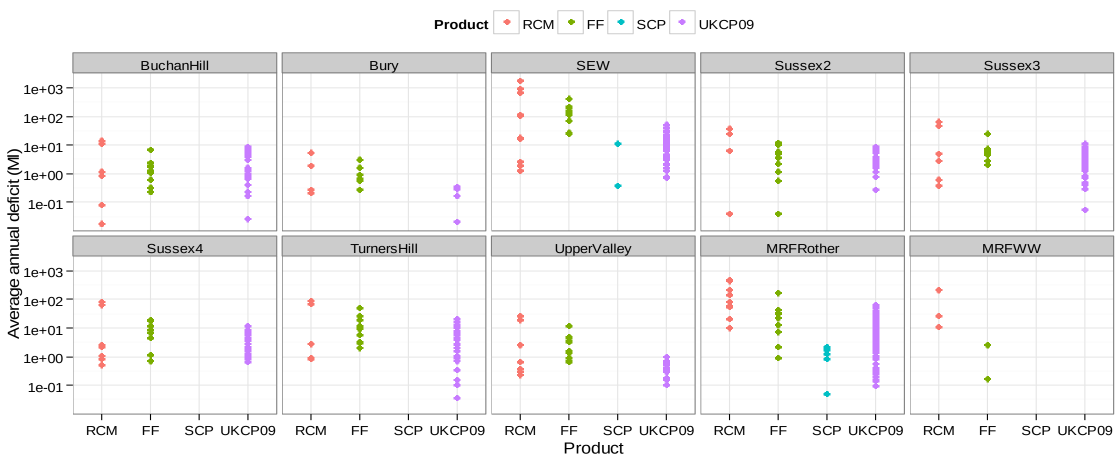


Figure 7.18 Deficit locations in the 2030s

The socio-demographic scenarios of the 2050s show further impacts to the study area under different demand profile (Figure 7.19 to Figure 7.22). Again the deficit mainly occurs in the Sussex North area, as the Sussex Worthing and Brighton area are more reliant on groundwater, and in this model, are less likely to be affected by changes in surface water supply from the River Rother and the River Medway (Weirwood reservoir).

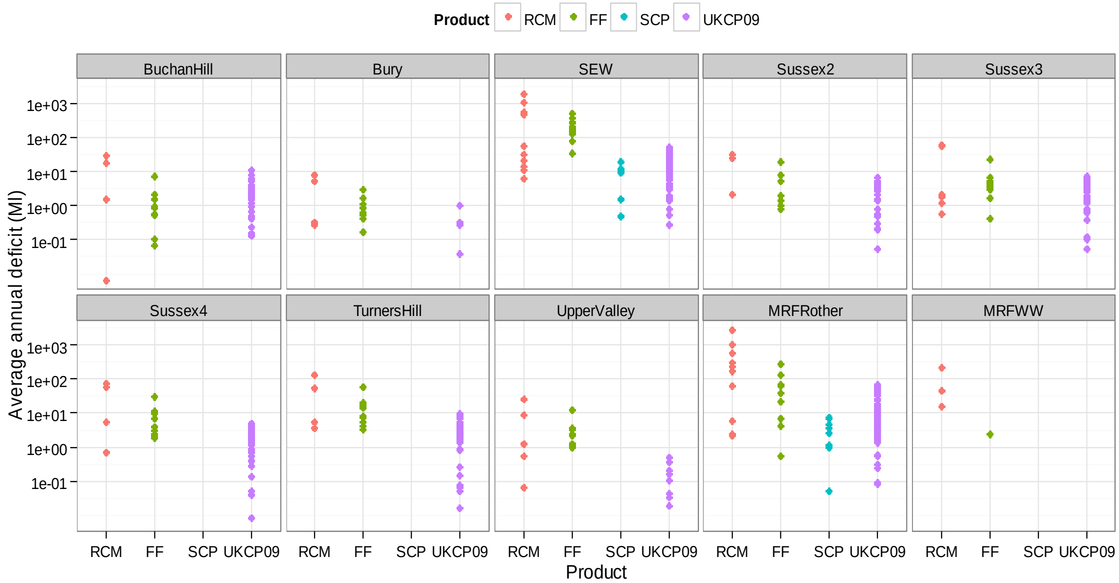


Figure 7.19 Deficit locations in the 2050s Innovation scenario

The Market Forces scenario, however, shows that with extreme water demand, the Brighton area (which consists of BrightonDem1, BrightonDem2 and Shoreham) and the Worthing area (represented by the WorthingDem node) could experience water deficit under all climate conditions. Network analysis further demonstrates that under such situation, the nodes with fewer accesses to alternative supplying sources are likely to fail. In the case of the Market Forces scenario, each region of the study area could also become highly localized in its supply, as there is little spare capacity to transfer water to other regions. Therefore the coast transfer link between the Sussex North area and the Worthing area will become less necessary.

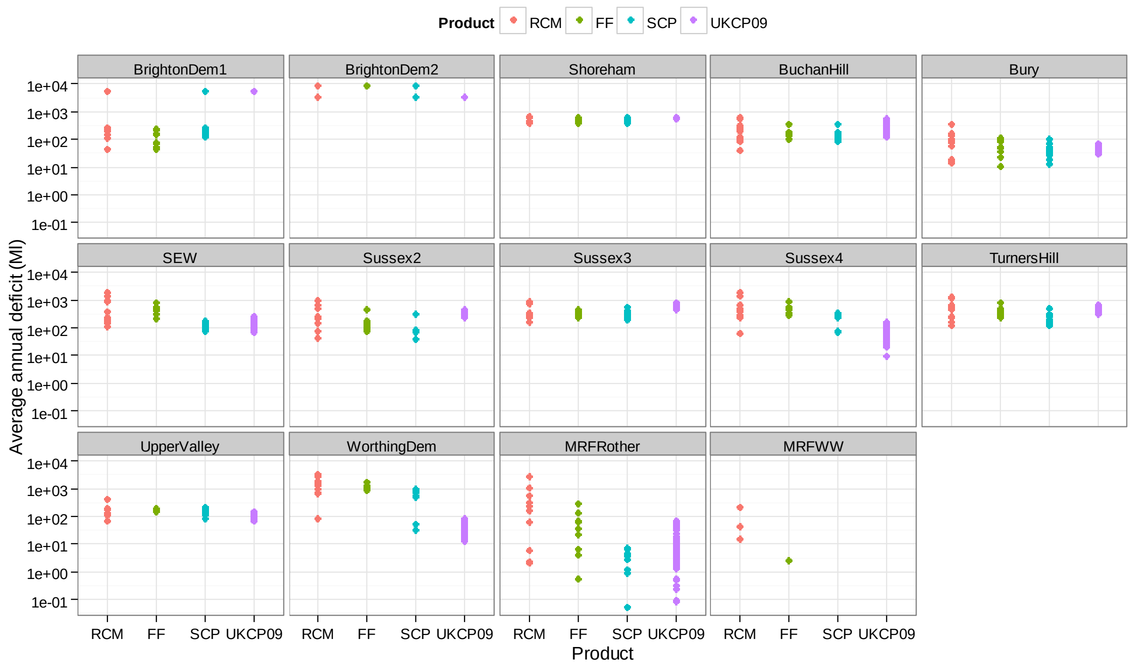


Figure 7.20 Deficit locations in the 2050s Market Forces scenario

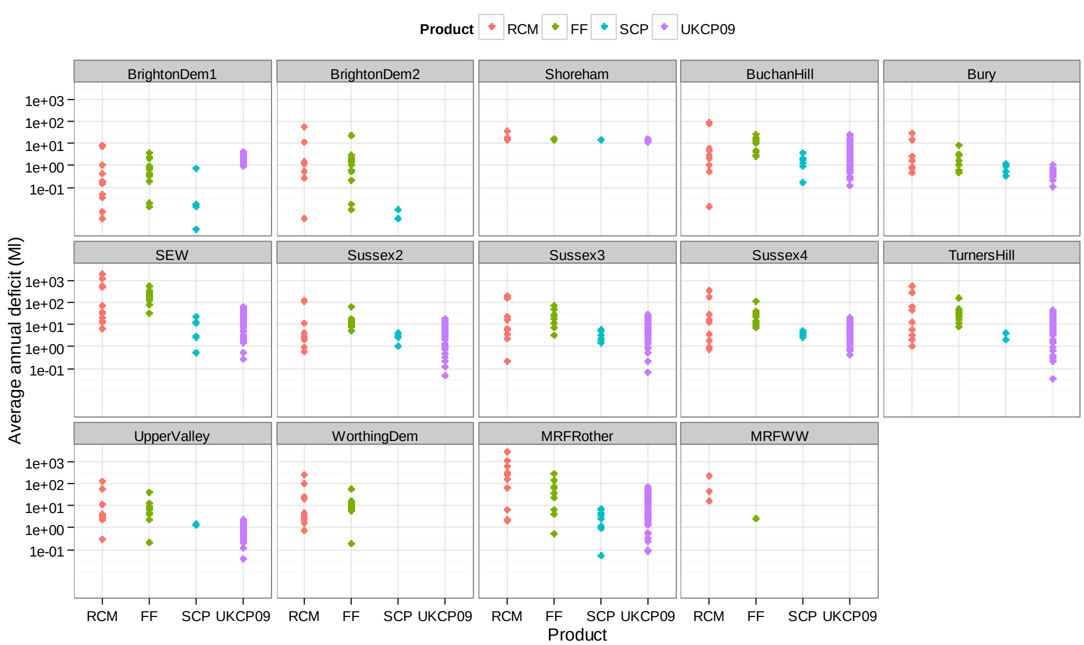


Figure 7.21 Deficit locations in the 2050s Local Resilience scenario

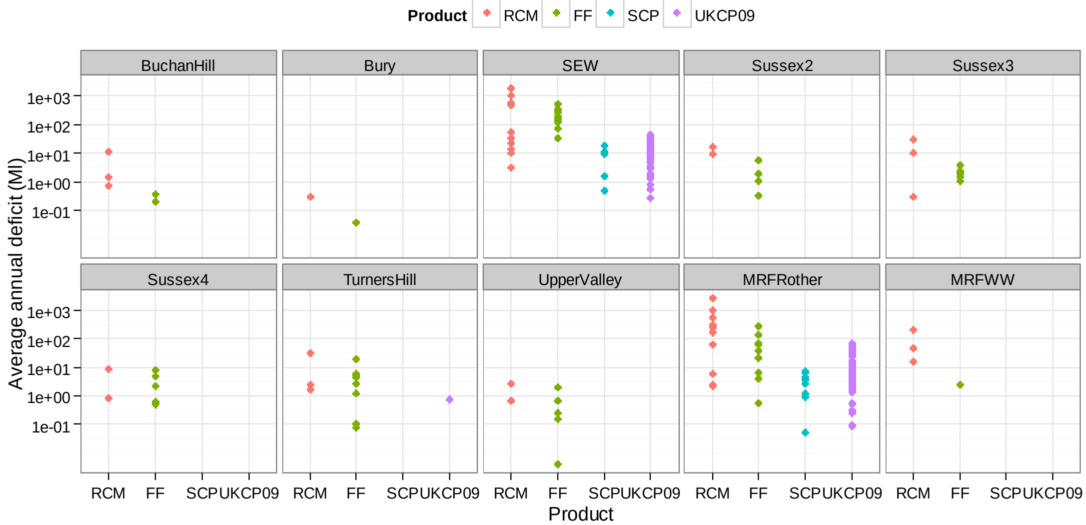


Figure 7.22 Deficit locations in the 2050s Sustainable Behaviour scenario

7.3.5. Most severe droughts in each climate product

This section examines the main drought sequences that create significant deficits in each climate product. In essence, for each time period and demand profile, the worst drought year of each model ensemble/climate scenario is congregated into a list of unique drought years. For the RCM and FF group, these are the actual years in the time series sequence. For the UKCP09 and the SCP group, as the time series is the modified historic 1961-1990 period, the drought year was converted back to the corresponding year in that sequence. Table 7-4 and Table 7-5 show that for Sussex North overall the RCM and the FF group include different drought years, while the SCP and the UKCP09 product mostly test the supply system against variations of the 1976 and the 1988/1989 droughts (for similar tables of Worthing and Brighton, refer to Appendix C). As such, since Sussex water resource system faces a less varying pattern of droughts under the UKCP09 and the SCP products. This is explained by the data format of the climate products and also partially explains why despite containing a wider range of changes (100/1000 scenarios) than the RCM and the FF group, the Sussex system performs more robustly under the UKCP09 climate conditions than the RCM and FF conditions. Therefore, varying time series like the RCM and the FF group appears to be useful to test system performance under different types and sequences of droughts. It was further noted that while FF is a downscaled product of the RCM, it seems to retain the drought patterns of RCM, with the most severe drought years of the RCM group also largely constituting the severe drought list of the FF group.

Table 7-4 Sussex drought year-Optimisation Model

Period	Demand Profile	RCM	FF	SCP	UKCP09
2020s	Southern Water Base case	2010,2012,2013,2014, 2015,2025,2027,2031	2011,2012,2026,2031, 2032,2034,2035,2036, 2037	1988	1976,1988, 1989,1990
2030s	Southern Water Base case	2021,2022,2025,2028, 2032,2033,2040,2044, 2046	2023,2026,2031,2032, 2035,2036,2037,2045, 2049	1988	1976,1988, 1989
2050s	Innovation	2040,2041,2042,2044, 2057,2060,2065,2068, 2069	2044,2051,2054,2055, 2057,2058,2059,2066, 2067	1988,1989	1976,1988, 1989
2050s	Market Forces	2041,2044,2047,2049, 2057,2058,2067,2068, 2069	2044,2055,2056,2058, 2065,2067,2068	1976,1989	1976
2050s	Local Resilience	2040,2043,2044,2057, 2060,2064,2065,2066, 2068,2069	2044,2051,2055,2057, 2058,2059,2066,2067, 2068	1976,1988	1968,1976, 1987,1988, 1989
2050s	Sustainable Behaviour	2040,2041,2042,2051, 2053,2057,2065,2067, 2069	2040,2044,2045,2051, 2054,2055,2058,2059, 2066,2067	1988,1989	1971,1973, 1975,1988, 1989

Table 7-5 Sussex drought year-Simulation Model

Period	Demand Profile	RCM	FF	SCP	UKCP09
2020s	Southern Water Base case	2012,2021,2026,2031, 2033,2034	2012,2018,2026,2031, 2032,2035,2036,2037	1976	1976
2030s	Southern Water Base case	2025,2026,2031,2033, 2034,2048	2026,2031,2032,2035, 2037,2040,2044,2045, 2046,2049	1976	1976
2050s	Innovation	2050,2055,2057,2058, 2060,2062,2066,2067	2044,2049,2052,2054, 2058,2065,2066,2067	1976	1976
2050s	Market Forces	2040,2044,2045,2047, 2057,2058,2061,2066	2044,2045,2051,2055, 2058,2066,2067,2068	1976	1976,1989
2050s	Local Resilience	2040,2041,2058,2062, 2066,2067	2044,2045,2051,2055, 2056,2058,2066,2067	1976	1976

2050s	Sustainable Behaviour	2042,2044,2045,2066	2044,2052,2054,2058, 2065,2066,2067	NA	1976

The drought year tables further show that the Sussex North area is largely influenced by surface water droughts, in particularly the varying inflows of the River Rother. The Brighton and the Worthing area appear to be more insulated to the surface drought risks, due to their groundwater-dependence. It is not within the scope of this study to consider groundwater droughts; however, given the Chalk geology of the area, it is highly likely that the groundwater supply will also be affected by diminishing inflows. Therefore, the actual drought and supply deficit risks in Sussex Brighton and Sussex Worthing are likely to be higher than projected by the models.

7.4.CONCLUSION

In conclusion, this chapter has explored the uncertainty of alternative water resource model structure and socio-economic scenarios on top of climate uncertainty. It has demonstrated that climate uncertainty is still a significant influence; however water demand is quickly becoming a controlling factor once the 2007 demand level increases past the 35% threshold. The optimisation and the simulation models perform relatively well compared to the reference Aquator model of the managing water company. Both models demonstrate a gradual increasing risk of supply deficit in the 2020s and the 2030s; the risks vary widely in the 2050s and are highly dependent on the socio-economic scenarios.

The model shows that in order to avoid frequent supply failures in the 2050s, it is essential to maintain the *status quo* or lower demand profile. The socio-economic scenarios indicate that such reservation can only occur under sustainability-led governance or socially responsible consumerism (such as the Innovation or Local Resilience scenarios). On the other hand, if governance is growth-led and consumerism is individualistic, the system will face significantly high risks of water supply deficit to all the areas. The models do not consider groundwater drought risks, which may affect the groundwater-dependent Brighton and Worthing areas. Thus the future failure risks are mainly distributed within the Sussex North area, with the exception of the Market Forces scenario. However, given the Chalk geology of the area, it is likely that Brighton and Worthing will experience supply deficit during prolonged surface water droughts.

Finally, the cross-climate product analysis shows that the Sussex system is relatively robust under different variations of the 1975/1976 and the 1988/1989 droughts, possibly due to the usage of these historic event as the design event of drought planning. The system, however, is less immune to other, potentially new, sequence of droughts as projected in the RCM and the FF group. While the FF group is a downscaled and bias-corrected product of the RCM ensembles, its impacts on water deficits are quite similar to the RCM groups, which are much drier time series. The system is overall sensitive to the actual sequence of droughts and the low flow levels. It is therefore suggested that while UKCP09 contains the most wide ranging climatic conditions and possible changes, the actual historic-based application of the product limits its utility in testing system robustness. Therefore, aside from exploring alternative scenarios (as suggested in the Robust Decision Making framework), time series with diverse patterns are highly useful to test the system against surprise, particularly with regard to climate risks.

Chapter 8. WATER RESOURCE PLANNING UNDER UNCERTAINTY

8.1.INTRODUCTION

In the previous chapter, the vulnerability of the study area was explored under different demand and climate scenarios. Overall the area appears to be under various stresses, of which climate uncertainty and demand uncertainty are two influential ones. This chapter proceeds by analysing selected planning options of the area, and whether those options can accommodate the water demand of the area. It continues to follow the cascade of uncertainty as explored in previous chapters by using the four climate products as the inputs of a water resource planning system. Additionally, for the 2050s, it considers four alternative socio-economic scenarios leading to different levels of water demand. The chapter will mainly focus on the technical aspects of Decision Support System for decisions under uncertainty; further implications of the results on policy and adaptability of water resources planning to new patterns of risks will be discussed in detail in Chapter 9. First, Section 8.2 will describe the options and how they are analysed in the optimisation model. Second, Section 8.3 then presents and discusses the results, with in-depth analysis of the delivery network and the effectiveness of options in reducing supply vulnerability.

Planning decisions under the deep uncertainty of climate change and demand uncertainty is highly difficult. Arnell and Delaney (2006) outlined this adaptation process by four key points: impact awareness and concern, adaptation strategy, option selection and the influence of changes in the organisation characteristics, the regulation and the market on these factors. In the context of the UK, as described in Chapter 4, it involves revising a 25-year water resource plan, revised every five years. The focus of the plan, as typical of planning problems, does not only revolve just around the climate impacts; rather, it has to deal with a combination of stressors including water demand growth, supply reliability and the other socio-economic changes. Indeed, water demand management one of the core elements for water management to test the system robustness and reliability (Baumann et al., 1997; Butler and Memon, 2006). For water management in England and Wales, the headroom concept, the extra water supply capacity to accommodate unplanned demand, is often used in these plans to ensure system reliability and robustness. Based on these projected demand profiles, the water companies analyse their available options and select options to consider for the future. Apart from the UKCP02 and subsequently UKCP09 climate product, other products such as the Weather Generator, multi-model ensembles and Future Flows have also been used for risk analysis (Fowler et al., 2003; Christensen and Lettenmaier, 2006; Wilby and Harris, 2006; Fowler et al., 2007; Lopez et al., 2009b; Prudhomme and Davies, 2009). Many studies treat adaptation of the water planning system as a case of capacity expansion that accommodate the most likely projected demand (Jenkins et al., 2004; O'Hara and Georgakakos, 2008). Others like Lempert and Schlesinger (2000) and Wilby and Dessai () criticised this 'predict-then-act' approach and advocated a robust adaptation approach which considers all possible uncertainty and imaginable futures. There have been various methods of constructing the scenarios and time series. Lempert and Groves (2010) have used qualitatively different scenarios to test the robustness of water planning options under deep uncertainty. Paton et al. (2013) employed stochastic rainfall time series constructed from historical records while Manning et al. (2009) used the Bayesian statistical approach to construct the probability distribution of local climate change which provide the Thames catchment rainfall-runoff model with inputs to simulate future water abstraction availability. Yet, while the probabilistic approach can facilitate a risk-based assessment framework, New et al. (2007) argued that climate risks will change over time; similarly, Hall et al. (2007) stated that probabilistic climate scenarios may misrepresent uncertainty.

In terms of model choices, both optimization and simulation models have been used, such as AQUASIM (Huggenberger et al., 2013), IRAS (Matrosov et al., 2013), Watersim (Gober et al., 2010), Watercress (Paton et al., 2013). As discussed in Chapter 3, water resource planning can be formulated as a decision analysis problem in which the outcomes are selected on an optimisation or a satisficing basis. Alternatively, strategies can be selected via the use of simulation models, which follow operating rules specified by the users. These simulation models will then test the system and various strategies under the scenarios; via those tests, the users can analyse system performance based on their criteria and decide on the planning strategies. For adaptation under uncertainty, both the optimisation and the simulation approaches have been used to identify system vulnerability and robust strategies under varying conditions. The number of simulations tends to grow larger with the complexity of the model; on the other hand, the number of optimisation runs does not grow at the same order but the searching time may be prolonged due to the increasingly complexity of the response surface. Kasprzyk et al. (2012) further combined Sobol's variance decomposition with multi-objective evolutionary algorithms to generate the testing scenario and analyse system robustness. Meanwhile Matrosov et al. (2011) used a simulation model to test the conjunctive use of the Thames water resource system and Matrosov et al. (2013) compared an optimised plan with a Robust Decision Making plan to highlight the differences of these two approaches. However, to date, option analysis in water management and planning in England and Wales is still often separated from water resource modelling. Instead, the options are selected in a separate investment model which considers the average contribution to supply, financial investment and operational cost as well as the implementation duration. An integrated investment-water resource model is necessary since the actual supply of the option or demand reduction effects are dependent on the water supply network, as well as the nature of the supply deficits.

Based on that context, this chapter presents an example of using the optimisation model to select options based on the criteria of maintaining the minimum environmental flows and abating supply deficits with minimum operational cost. Firstly, Section 8.2 describes how the planning options were implemented in the simulation and optimisation model described in Chapter 7. It then outlines the planning options considered in the study and criteria for planning success. Secondly, Section 8.3 presents the option selected by the optimisation model, their comparative performance by the simulation model and the remaining vulnerability of the Sussex area under these plans. Section 8.4 then concludes with key points and results of the chapter.

8.2.METHODOLOGY

8.2.1. Problem formulation

In order to construct a Decision Support System for the study area, the problem is formulated as planning for a water supply network under climate change impacts. Due to changes in surface inflows, the region has to invest on strategies that augment supply, reduce demand or enhance transferring capacity. The study uses the optimisation model, a mathematical model which minimizes three criteria: total deficit in demand nodes, total deficit in environmental flows and the total financial cost of maintaining the best-possible water supply-demand balance. The problem is formulated as a mixed integer linear programming problem, with core decision variables of interest being binary variables that represents whether a strategy should be implemented or not.

The model is divided into two parts: a core model that represents physical relations between variables and a preferential model that searches for solutions based on the criterion preferences.

8.2.2. Core model specification

A core model usually contains given parameters, state variables, decision variables and constraints. In this study, as the focus is on a water supply network, the core model takes the form of a flow network that delivers water from sources to sinks. The model is formulated as a linear programming of which decision variables are not related via multiplication or division. For specific equations of the model, please refer to Appendix A.

8.2.3. Strategy representation

Planning strategies are represented as binary decision variable X_i (t) that will take the value of 1 if implemented during the time step *t* and 0 otherwise. Once implemented, the binary variable Use(X_i,t) presents whether the strategy is actually used, for instance in a time step if a desalination plant may have been implemented but does not supply water to the network, it will have X_{Desal}=1 and Use(X_{Desal})=0. Effects of the strategy onto the network include supply augmentation, demand reduction and changes on transfer capacity. Furthermore, options can be mutually exclusive, such as the implementation of one option will exclude another option, or have interactive effects. Decision variables that can provide additional supply are modelled as a fictional source that is not connected to other sources if the strategy is not implemented. This setup also allows calculating the real usage of the option (e.g. the supply provided by the decision variable and the frequency of source usage). Based on Southern Water 2009 Water Resource Management Plan, nine potential strategies were included in the model (Table 8-1). Strategies are characterized into non-permanent and permanent options: the former can be turned off once not needed (such as hosepipe ban measures) while the latter remains in place once implemented and incurs fixed operational cost even when they are not used. Strategies are also grouped into groups of mutually exclusive options. Hosepipe bans are governed by the rainfall-based SPI12. In essence, the model can choose to implement hosepipe ban up to 10% of the whole time series in time steps with SPI12 < -1.8. This condition was based on the Drought Plan of the study area (Southern Water, 2013).

Taking supply from supply nodes would incur a pumping cost, as described in Chapter 7. The cost is different for each source, which reflects their priority of abstraction and the actual financial cost. To avoid double counting, the pumping cost is only accounted in the immediate links to the source. Overall, surface water from River Rother would be the first supply source, followed by other groundwater (except Hardham) sources. Note that this is not the accurate pumping price; it was constructed to be similar to the real cost, but also the pumping priority of the source nodes. With nodes and links that can be modified by the Decision Variables, the cost includes additional operational cost

(OPEX) of the implemented strategies. Once an option is implemented, the cost also includes a one-off capital investment cost (CAPEX). All the pumping cost, OPEX and CAPEX are adjusted using a discount rate based on the Treasury Green book (Her Majesty's Treasury, 2013) of 5%. As such, the same amount of money in a later time step will have a lower cost than it is in an earlier time step.

$$NPV = \frac{Cost}{(1+p)^n}$$

Equation 8-1

in which n is the year of the time series, NPV is the Net Present Value and p is the discount rate

Therefore, the model will implement and activate strategies as later as possible, unless to mitigate deficits.

As described in Chapter 4, the study area consists of Sussex North, Sussex Worthing and Sussex Brighton. It has two inter-company water transfers: Southern Water provides South East Water with 5.4 Ml/day from the Weirwood Reservoir for and can receive up to 15 Ml/d from Portsmouth Water to the Hardham WSW. The V6 bidirectional link between Sussex North and Sussex Worthing can transfer up to 15 Ml/d in either direction while the Rockroad link from Worthing to Brighton can distribute up to 7 Ml/d. Under situation of water shortages, the available supply therefore can be transferred between Worthing and Sussex North, as well as from either of these zones to Brighton.

Table 8-1 List of single options selected from Southern Water's 2009 Water Resource Management Plan (Southern Water, 2009b) and used in the Optimisation Model

Option ID	**Option Name**	**Category**	**Effect**	**Limit of usages**	**CAPEX (million GBP)**	**Fixed OPEX (GBP/week)**	**Variable OPEX (GBP/Ml)**
HP	Hosepipe Bans	Non-permanent	Reduce demand by 10% with no demand metering, 5% with demand metering	Maximum implementation time: 10% of the whole time period; cannot be implemented from January-March	0	0	0
d1	Desalination Plan in the Brighton Area (CD1-20)	Permanent	Supply maximum 20 Ml/d to Shoreham and a part of Brighton	Mutually exclusive to d6	43	5,403	462
d2	98% universal metering	Permanent	Reduce demand by 10%	N/A	6	42,300	0
d3	Remove the constraint of 62 Ml/day transfer capacity from Hardham Water Treatment Plan	Permanent	Increase the transfer capacity from 62 Ml/day to 1062 Ml/day	N/A	3	300	138

d4	Arun Abstraction below tidal limit	Permanent	Supply up to 10 Ml/d to Hardham Water Treatment Plan	N/A	10	1,351	89
d5	Hardham Minimum Residual Flow (MRF) Reduction	Non-permanent	Reduce the environmental flow requirement by 20%	N/A	1	0	70
d6	Desalination Plant in the Brighton Area (CD1-10)	Permanent	Supply up to 10 Ml/d to Shoreham and part of Brighton	N/A	26	4,338	462
d7	Ford Effluent Re-Use with Biological Aerated Flooded Filter treatment	Permanent	Transfer 20 Ml/d of treated effluent to Hardham Water treatment plan	N/A	34.560	3,547	122
d8	Hardham Wellfield Optimisation	Permanent	Supply up to 4 Ml/d to Hardham Water treatment plan	N/A	8.385	0	45
d9	Aquifer Storage and Recovery	Permanent	Supply up to 8 Ml/d to the Worthing area	Can only be used for up to16 weeks per year	13.885	870	100

Figure 8.1 depicts the schematic of the Sussex water resource system with available planning options and their locations. The Brighton area and the Worthing area are shown within the corresponding boxes, and the remained nodes belong to the Sussex North area. The water resource planning options can alleviate supply-demand deficit in the area by universally reducing water demand (Option d2) or locally increasing supply in Sussex North (d4, d7, d8), Sussex Brighton (d1 and d6) and Sussex Worthing (d9). In dealing with potential bottlenecks of the network, option d3 can augment the transferring capacity from the Hardham Water Treatment Plan into the Sussex North area. Many of the options can contribute supply into the Hardham Water Treatment Plan, which has a maximum capacity of 75 Ml/d. Additionally, the treatment capacity reduces to 40 Ml/d if Rother flows exceed 500 Ml/d, which is a constraint also implemented in the model.

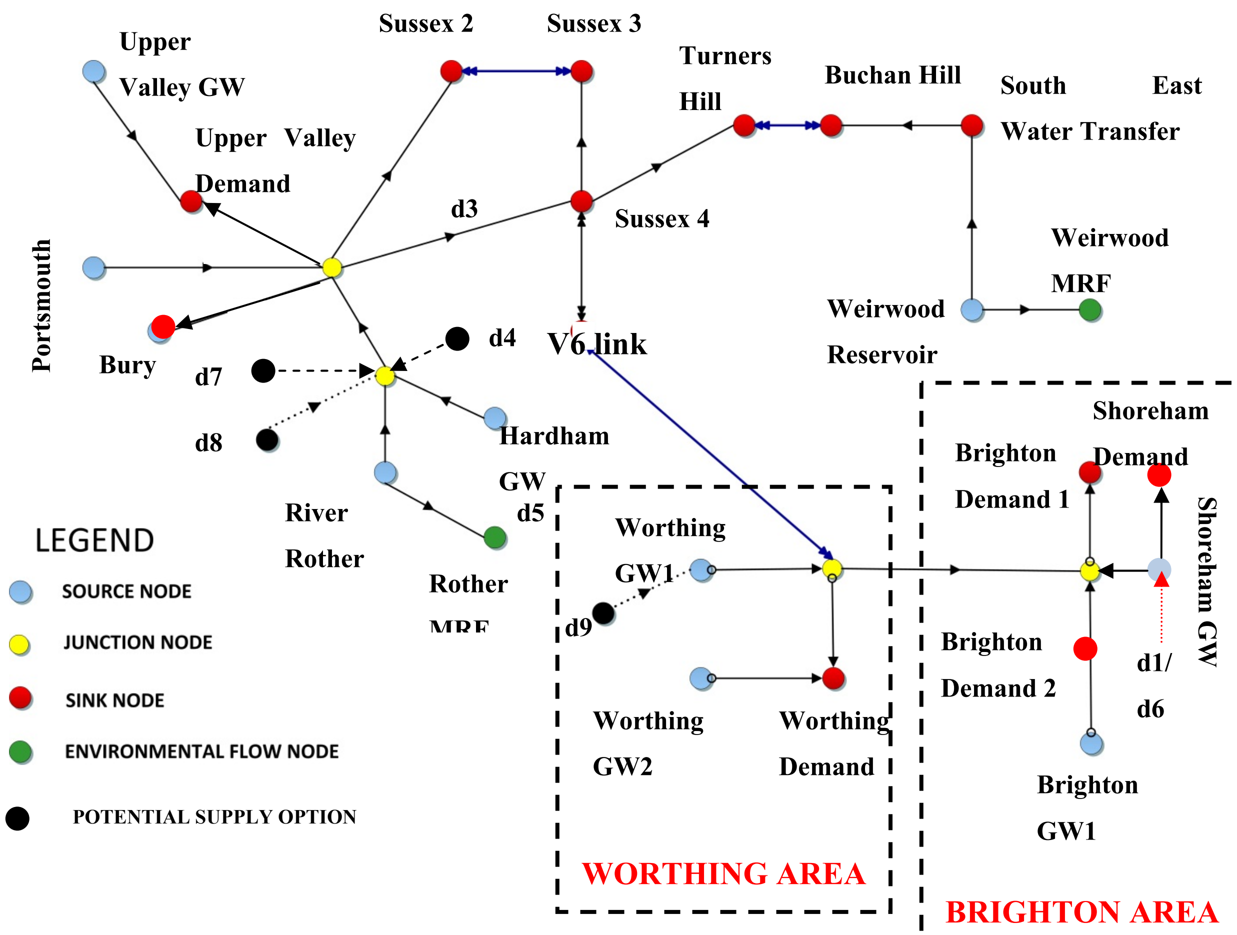


Figure 8.1 Schematic of the Sussex Optimisation Model with available water planning options

8.2.4. Criteria

The set of criteria considered for minimisation in this study are

- **Summation of deficit occurring in demand nodes** (set D ⊂ N) within one run

$$\mathrm{Deficit(n,t)} = \mathrm{Supply}(n,t) - \mathrm{Demand(n,t)}$$

Equation 8-2

$$\boldsymbol{C_1} = \sum_{\mathbf{t}} \sum^{\mathbf{D}} \mathbf{Deficit(n,t)}$$

Equation 8-3

- **Sum deficit of environmental flows** (set E ⊂ N) within one run

$$C_2 = \sum_{\mathrm{t}} \sum^{\mathrm{E}} \mathrm{Deficit}(n,t)$$

Equation 8-4

- **Total operational cost (of existing sources and implemented strategies)** Water supply to the system can either come from existing sources or from options implemented by the decision variables. As the focus of the study is on potential implementation of new decision variables, the fixed operational cost of existing sources are not considered in the calculation. Furthermore, when comparing across the scenarios, the operational cost of existing sources does not change and thus is not necessary to be included.

Overall the objective of the model is to minimise these three criteria. As reducing water deficit and minimising pumping cost are conflicting objectives, multiple criteria analysis is used. The model can operate in two modes: i) Aspiration-Reservation based Multi-criteria analysis, in which the decision makers state their desirable criterion range and the model will select a feasible solution that is closest to the desirable values, and

ii) Ranked Optimisation, in which the model optimises from the most prioritised criterion to other criteria. As described in Chapter 7, expert judgement by relevant decision makers indicated a preference for the latter method. Therefore this chapter continued to use the second mode to select the preferred planning option for each scenario. In particular, the model first minimises possible environmental flow deficits, then reruns with that minimum value to search for the minimum possible demand deficits. It is thus a process of selecting from multiple options with the minimum environment flow deficits, then choosing amongst them for ones with the minimum demand deficit and then selecting the one with the least cost. Finally the model searches for a solution with minimum overall cost while maintaining that minimum deficits on environmental flows and demand.

8.2.5. Scenarios

The scenarios follow those of Chapter 7, which uses four different climate products and socio-economic scenarios from Southern Water and the EA. Additionally, for each scenario, the testing set will include a headroom demand uncertainty, in which non-environmental demand is increased by 5%, and a headroom demand-groundwater outage uncertainty, in which the demand is at the headroom level and groundwater supply is reduced by 5% due to outages.

8.2.6. Robust Decision Analysis using the Simulation Model

Due to the time and computational constraints, the study could not use the Simulation Model to analyse the 512 possible sets of options. Therefore, the Optimisation Model was used to reduce the number of options. In this step, all options selected by the Optimisation Model in the 2020s, 2030s and 2050s for each demand scenario will be rerun by the Simulation Model. This produces a basis for comparison of sub-optimal options overall, to identify the other potentially robust packages of options that can satisfy the acceptable level of cost and supply deficit. Analysis of the whole packages rather than selecting the optimal option for the majority of scenarios will reduce the risks of selecting non-robust options. This approach has been described in more detail in Chapter 3, in particular Section 3.2.

8.3.RESULTS AND DISCUSSION

8.3.1. Option Selection

The results show that using the potential options under optimisation, the system can successfully cope with the demand increase. Since none of the options can augment the environmental flows, the values of the environmental flows remain the same as in Chapter 7 (refer to Figure 7.16a). In terms of deficit, Figure 8.2 depicts that under the Base case, supply deficit of even the most extreme 2050s socio-economic scenario- the Market Forces scenario-still remains similar to that of other 2050s demand scenarios. The major variation of average annual deficit occurs across different climate products, and as such depicts that climate post-processing is the major uncertainty factor in the uncertainty cascade under the Base Case socio-economic scenario.

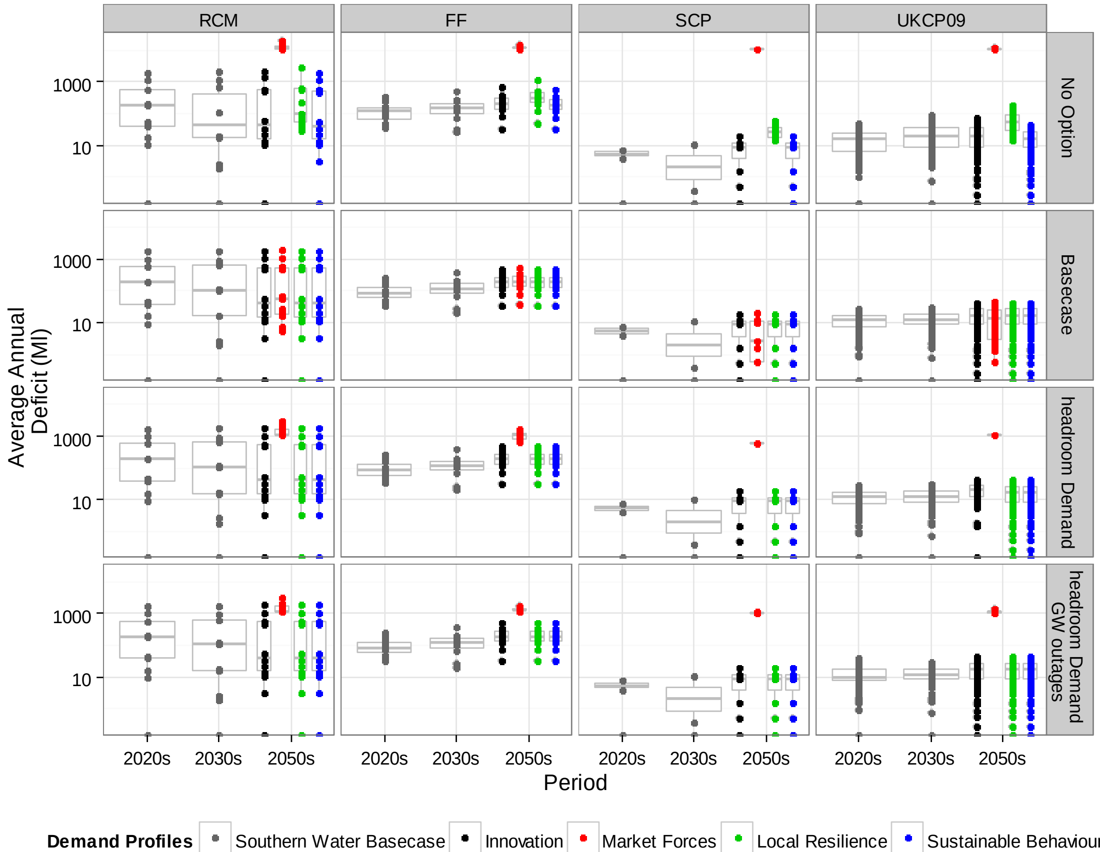


Figure 8.2 Supply deficit without options, in the Base Case scenarios, with headroom Demand (5% increase from the Base Case demand), and with headroom Demand and 5% groundwater reduction due to outages

However, the system is vulnerable to additional pressure from demand and groundwater outages. In essence, with 5% of extra demand (the Headroom Demand scenario), the system under the Market Forces scenarios again swings to ubiquitous supply failures and even more so if the groundwater sources diminish by 5% (the scenario of Headroom Demand coupled by Groundwater outages).

In terms of financial cost to maintain the system, higher demand profiles also lead to the need for strategy implementation, thus raising the overall cost due to the additional pumping cost from the current sources and from investments in the new strategies. For instance, the average annual cost (including discounted option implementation cost) for the current water resource system, which is yet without any strategy implementation, is much lower than when the options are implemented to cope with the base case demand, the headroom demand and the additional pressure from groundwater outages (Figure 8.3).

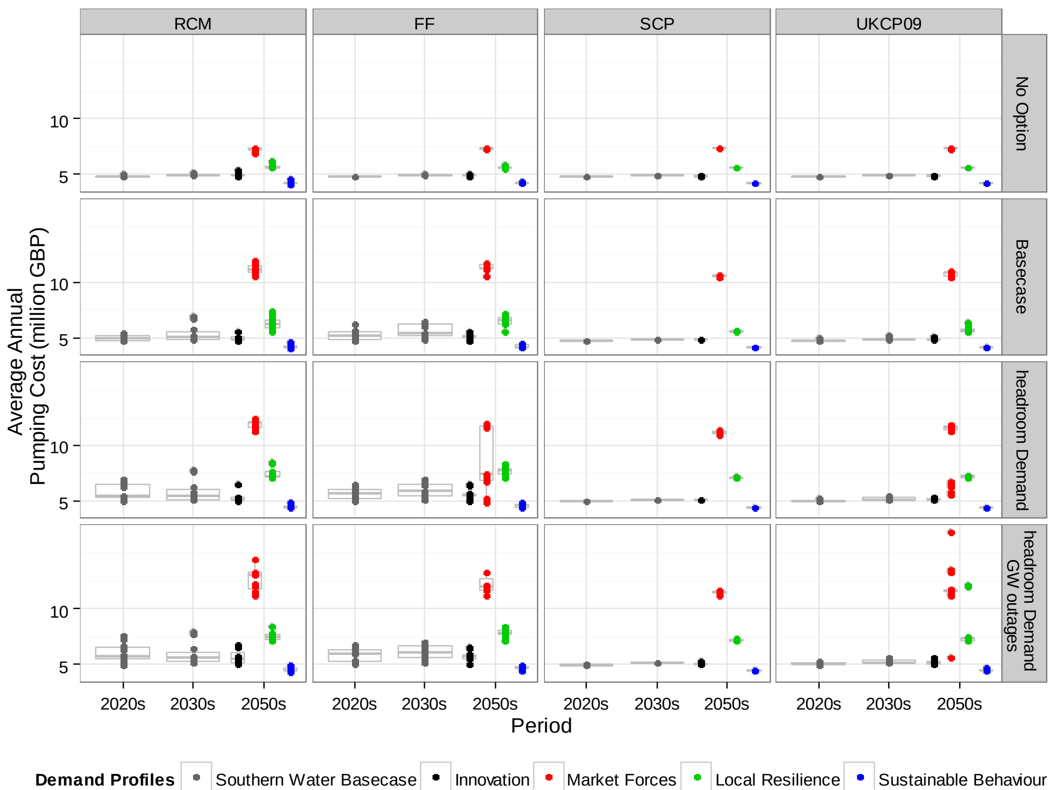


Figure 8.3 Average annual cost of maintain low supply deficits in the water resource system in Sussex

The number of selected options tends to increase with increasing demand. Overall, the model selected in total 39 unique option combinations, as presented in Table 8-2.

Table 8-2 Unique combinations of the options. 0 denotes not selecting any option.

Period	NodeProf	Test Scenarios	RCM	FF	SCP	UKCP09
2020s	SW Projections	Base Case	0,d4,d4-d8,d8	0,d2-d4-d8,d4,d4-d8,d7,d8	0	0,d8
		Headroom Demand	0,d2,d2-d4-d8,d2-d8,d4,d8	0,d2-d4-d8,d4,d4-d8,d7,d8	0	0,d2,d4,d8
		Headroom Demand GW outages	0,d2,d2-d4-d7,d2-d4-d7-d8,d2-d8,d4,d4-d8	0,d4,d4-d7,d4-d7-d8,d4-d8,d7,d7-d8	0	0,d2,d4,d8
2030s	SW Projections	Base Case	0,d2,d2-d4-d8,d4,d8	0,d2-d4-d8,d4,d7,d8	0	0,d2,d4,d4-d8,d8
		Headroom Demand	0,d2-d7,d2-d8,d4,d4-d8,d8	0,d4,d4-d7,d4-d8,d7,d7-d8	0	0,d2,d4,d8
		Headroom Demand GW outages	0,d2-d4,d2-d4-d7-d8,d2-d7,d4,d4-d8,d8	0,d4,d4-d8,d7,d7-d8	0	0,d2,d4,d4-d8,d8
2050s	Innovation	Base Case	0,d2-d4,d4-d8,d8	0,d4,d4-d8,d8	0	0,d8
	Market Forces	Base Case	d1-d2-d4-d7-d8-d9,d1-d2-d4-d7-d9,d1-d2-d4-d8,d1-d2-d4-d8-d9,d1-d2-d7-d9,d1-d2-d8-d9,d1-d2-d9	d1-d2-d4-d7-d8-d9,d1-d2-d4-d7-d9,d1-d2-d7-d8-d9,d1-d2-d9	d1-d2-d4,d1-d2-d4-d7,d1-d2-d4-d7-d9,d1-d2-d4-d8,d1-d2-d4-d9,d1-d2-d8	d1-d2,d1-d2-d4,d1-d2-d4-d7,d1-d2-d4-d7-d8,d1-d2-d4-d8,d1-d2-d4-d8-d9,d1-d2-d4-d9,d1-d2-d7,d1-d2-d7-d8,d1-d2-d8
	Local Resilience	Base Case	0,d2,d2-d4-d8,d2-d7,d2-d7-d8,d4-d7,d4-d8,d8,d8-d9,d9	0,d2-d4,d2-d4-d8,d2-d4-d8-d9,d2-d7-d8,d4-d8-d9,d7-d8,d7-d8-d9	0,d2	0,d2,d2-d4,d2-d8,d4,d4-d8,d4-d8-d9,d8
	Sustainable Behaviour	Base Case	0,d2,d4-d8,d8	0,d8	0	0
	Innovation	Headroom Demand	0,d2-d4,d4,d7	0,d2-d4-d8,d4,d4-d8,d7	0	0,d4,d8
	Market Forces	Headroom Demand	d1-d2-d4-d7-d8-d9,d1-d2-d4-d7-d9,d1-d2-d4-d8-	d1-d2-d4,d1-d2-d4-d7-d8-d9,d1-d2-d4-d7-d9,d1-d2-d9	d1-d2-d4,d1-d2-d4-d8,d1-d2-d4-d8-d9,d1-d2-d7,d1-d2-	d1-d2-d4-d7-d8-d9,d1-d2-d4-d7-d9,d1-d2-d4-d8-

			d9,d1-d2-d7-d8-d9,d1-d2-d7-d9,d1-d2-d9		d7-d8	d9,d1-d2-d4-d9,d1-d2-d7-d8-d9,d1-d2-d7-d9,d1-d2-d8-d9
	Local Resilience	Headroom Demand	d2,d2-d4,d2-d4-d6-d7-d8,d2-d7,d2-d7-d8	d2,d2-d4,d2-d4-d7,d2-d7,d2-d7-d8	d2	d2,d2-d4,d2-d8
	Sustainable Behaviour	Headroom Demand	0,d4	0,d4,d8	0	0
	Innovation	Headroom Demand GW outages	0,d2,d2-d4,d2-d4-d8,d2-d7,d4-d8,d7	0,d2-d4,d2-d4-d8,d4,d4-d7,d4-d8,d7	0,d8	0,d2,d4,d4-d8,d8
	Market Forces	Headroom Demand GW outages	d1-d2-d3-d4-d7-d8-d9,d1-d2-d4-d7-d8-d9,d1-d2-d4-d7-d9,d1-d2-d4-d8-d9,d1-d2-d7-d8-d9	d1-d2-d4-d7-d8-d9,d1-d2-d8-d9	d1-d2-d4-d7-d9,d1-d2-d4-d8-d9,d1-d2-d7-d8-d9,d1-d2-d7-d9	d1-d2-d3-d4-d7-d8-d9,d1-d2-d4-d7-d8-d9,d1-d2-d4-d7-d9,d1-d2-d4-d8-d9,d1-d2-d4-d9,d1-d2-d7-d8-d9,d1-d2-d7-d9
	Local Resilience	Headroom Demand GW outages	d2,d2-d4,d2-d4-d7-d8,d2-d4-d8,d2-d7-d8,d2-d8	d2,d2-d4-d7,d2-d4-d8,d2-d7,d2-d7-d8	d2,d2-d8	d1-d2-d3-d4-d7-d8-d9,d2,d2-d4,d2-d4-d8,d2-d8
	Sustainable Behaviour	Headroom Demand GW outages	0,d4,d8	0,d4,d8	0	0,d8

The table shows that using different climate products can lead to different option selection, even under the same socio-economic scenario and within the same time period. In particular, due to the relatively less severe climate conditions of the SCP product, the water resource system does not often need additional planning options. For 2020s, Figure 8.4 shows the frequency of the portfolio being selected in the scenarios and Figure 8.5 shows how often on average an option is actually used if it is implemented by the optimisation model. The figures further show how option selection for a robust system varies under the uncertainty projected by different climate products and socio-economic scenarios. In particular, the RCM product will lead to early implementation of either the d4 (Arun Abstraction) option or d8 (Wellfield Optimisation) or a combination of both. In order to supply for the headroom demand, which is 5% higher than the baseline, the addition of the d2 option (universal metering) becomes necessary. If groundwater sources become unreliable at a rate of 5% outage, the system will either need higher utilisation of the options, or the addition of d7 (Ford Effluent Reuse).

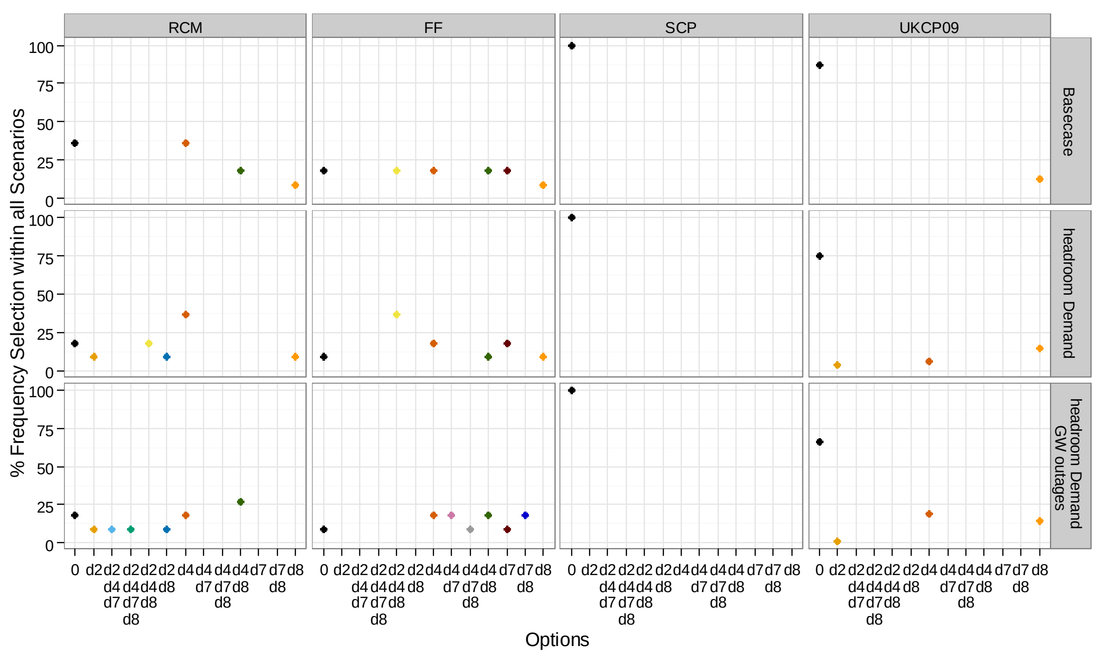


Figure 8.4 Selection frequency graph of the option portfolio in 2020s. Each point represents the frequency of the option being selected in 11 scenarios for the RCM, FF and SCP products and in 100 scenarios for the UKCP09 product. 0 represents no selected option.

Overall, the Arun Abstraction option appears to be the most frequently selected option, followed by universal metering and Wellfield Optimisation. Meanwhile, if the FF product is used as the information source, the set of options selected include universal metering and effluent reuse even under the baseline demand. These option sets remain quite stable under the headroom demand and the extra pressure of groundwater outages. However, under the prospect of groundwater outages, the selected options do not include universal metering anymore and instead switch to additional supply from effluent reuse (d7). The SCP product, on the other hand, projects little water deficit in the 2020s, and as a result, does not need any strategies to adapt. Similarly, the UKCP09 scenarios mostly does not require any option implementation, although certain scenarios amongst the set do indicate the need of implementing a single adaptation strategy, either from universal metering, Arun abstraction or effluent reuse.

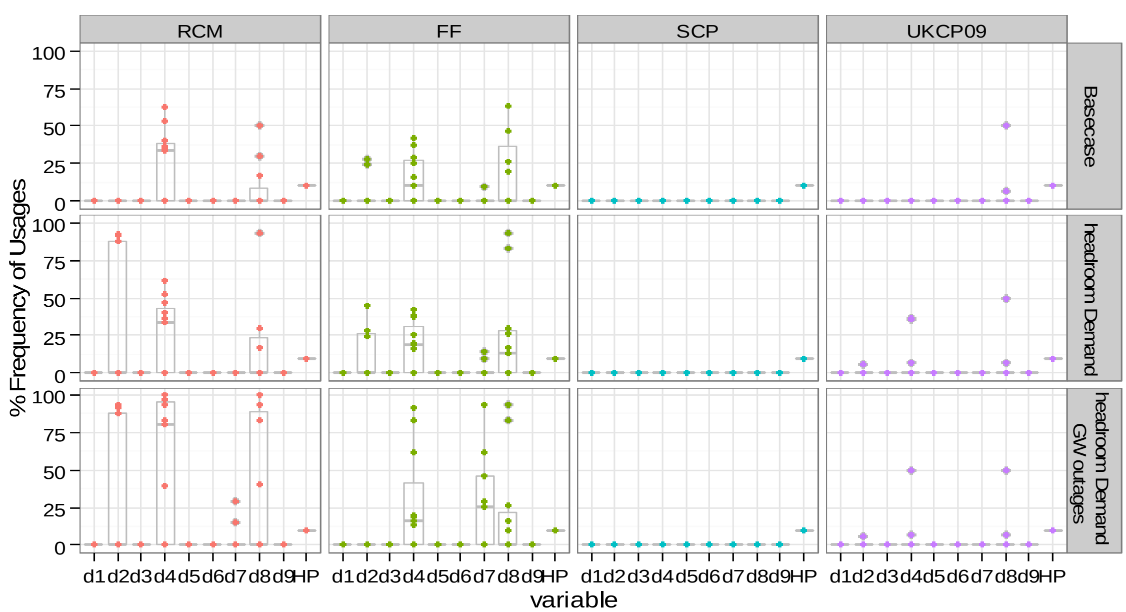


Figure 8.5 Frequency of usage of each option overall in 2020s. The box plots at the background show the 25th, 50th and 75th percentiles of the usage frequency of each option and the points present the actual usage frequency under each scenario.

Since none of the activated options can modify environmental deficit, that environmental deficit remains the same in each scenario. Furthermore, maintaining environmental flows is the top priority in the optimisation process and therefore is not compensated for any competing water demand. Therefore the environmental deficit criterion becomes an index that can indicate how dry the climate scenario is. In essence, if environmental deficit is large, this indicates frequent low values of surface flows and hence little surface water left to top up the reservoir and provide water for other demand nodes. When environmental deficit is plotted against the pumping cost and the supply deficit, there seems to be a preferential structure of how the Optimisation Model selected the options. For instance, for the 2020s climate conditions projected by the UKCP09 product, the Optimisation Model has indicated either maintaining the current water resource system without any changes (0), 98% universal metering (d2), Arun abstraction (d4), and Hardham Wellfield Optimisation (d8).

Figure 8.6 shows the relationship of the model selection with the dryness of the scenario, as indicated by environmental deficit. In the scenarios of sufficient surface flows, the Optimisation Model indicated inaction is the best plan; yet once water shortages occurs, the model starts to select Wellfield Optimisation (d8-the cheapest option to implement), Arun Abstraction (d4) and subsequently universal metering (d2). While the preferential order of option selection remains quite consistent across the scenario of Base case, Headroom Demand and additional Groundwater Outages, the climate conditions that prompt the switch in plan, which Brown et al. (2012) referred as the **decision sensitive conditions**, do shift in response to the pressure of additional demand and reduced groundwater supply.

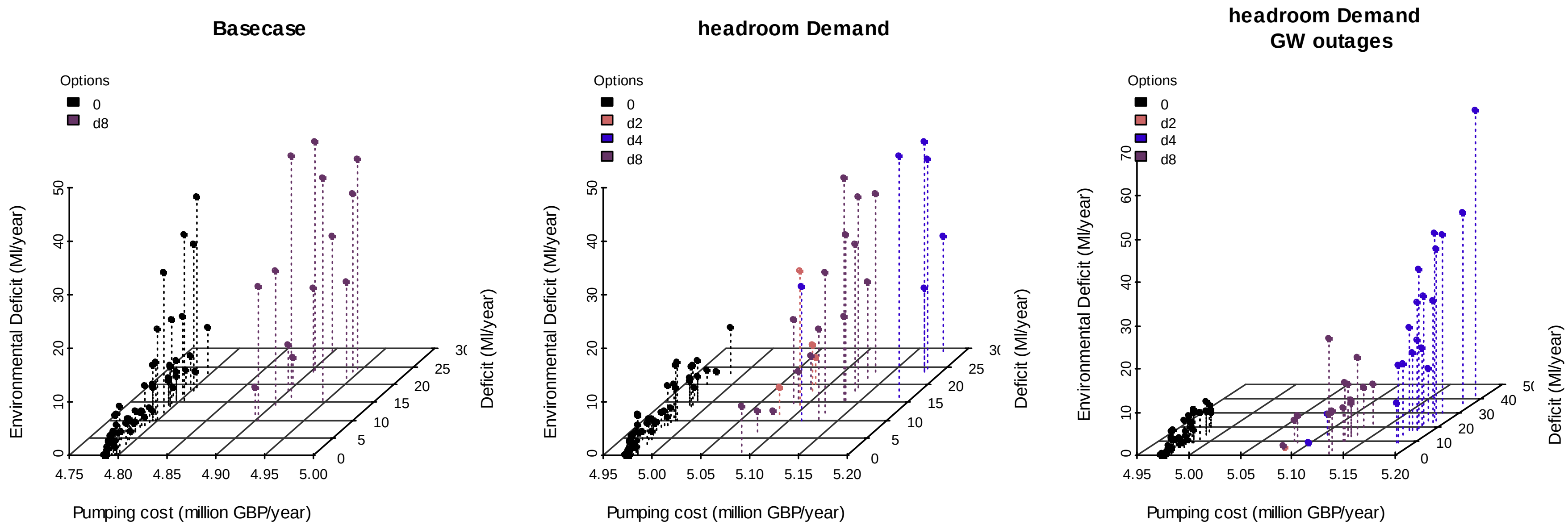


Figure 8.6 Three-dimensional plot of Environmental Deficit versus Pumping Cost and Supply-Demand Deficit in 2020s for the UKCP09 product

In the 2030s, the different climate products still lead to different option selections, partly due to the dryness and the decision sensitive conditions they project. The option sets still mainly contain the portfolio of the 2020s. Again, the SCP product appears to be the least severe climate projection and does not indicate the need to adapt. Similarly, the majority of the UKCP09 scenarios do not require any additional investment, with very few needs to rely on d2, d4 or d8. On the contrary, the RCM and the FF product continue to project testing conditions for the system to adapt. However, while the RCM conditions make the system more dependent on d4, the FF conditions seem to prefer the d7 option.

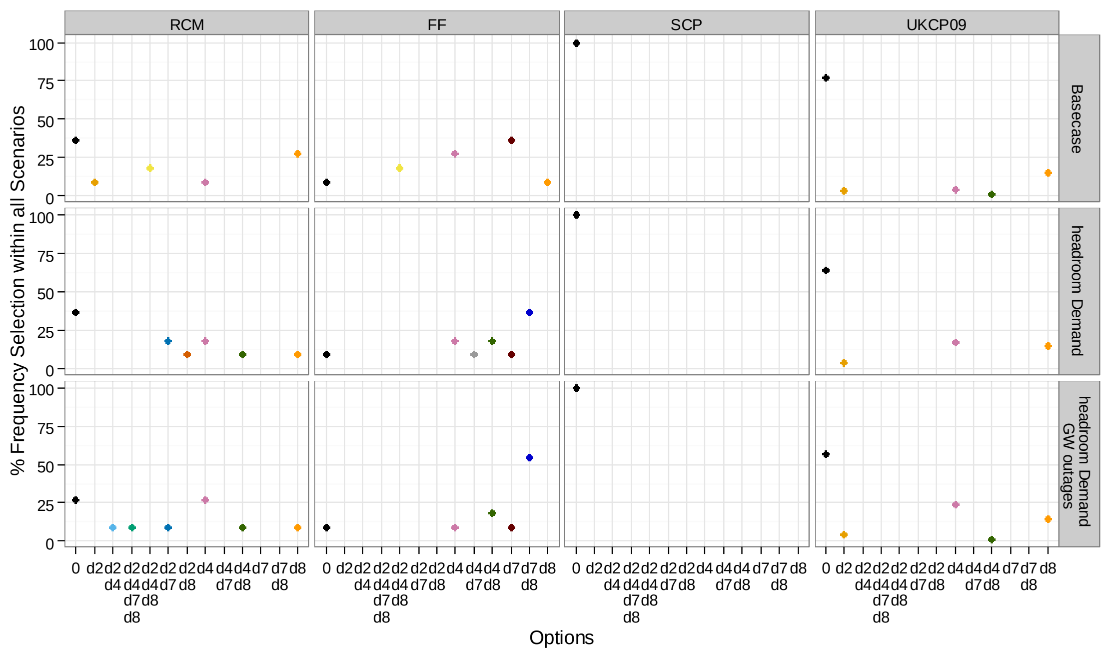


Figure 8.7 Frequency graph of the option portfolio in 2030s

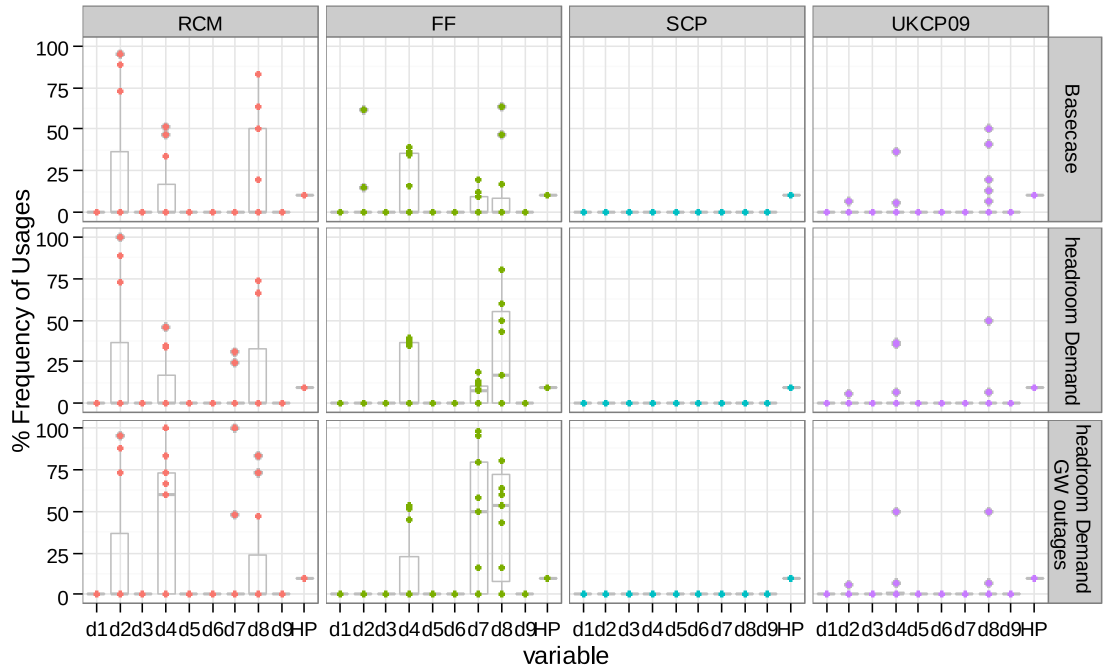


Figure 8.8 Overall frequency of usage for the selected option in 2030s

A comparison between the option preference under the FF and the RCM products (Figure 8.9) depicts that the option selection is determined by the level of environmental deficit in the scenario, but also dependent on the climate product. While the RCM conditions are considerably drier than those of FF, under RCM, the optimised Sussex water operation has a slightly different response structure than under FF. For instance, under the Headroom Demand-Groundwater outages, d7-d8, the combined portfolio of Arun Abstraction and Wellfield Optimisation, appeared in the selected portfolio for the FF product but not for the RCM product.

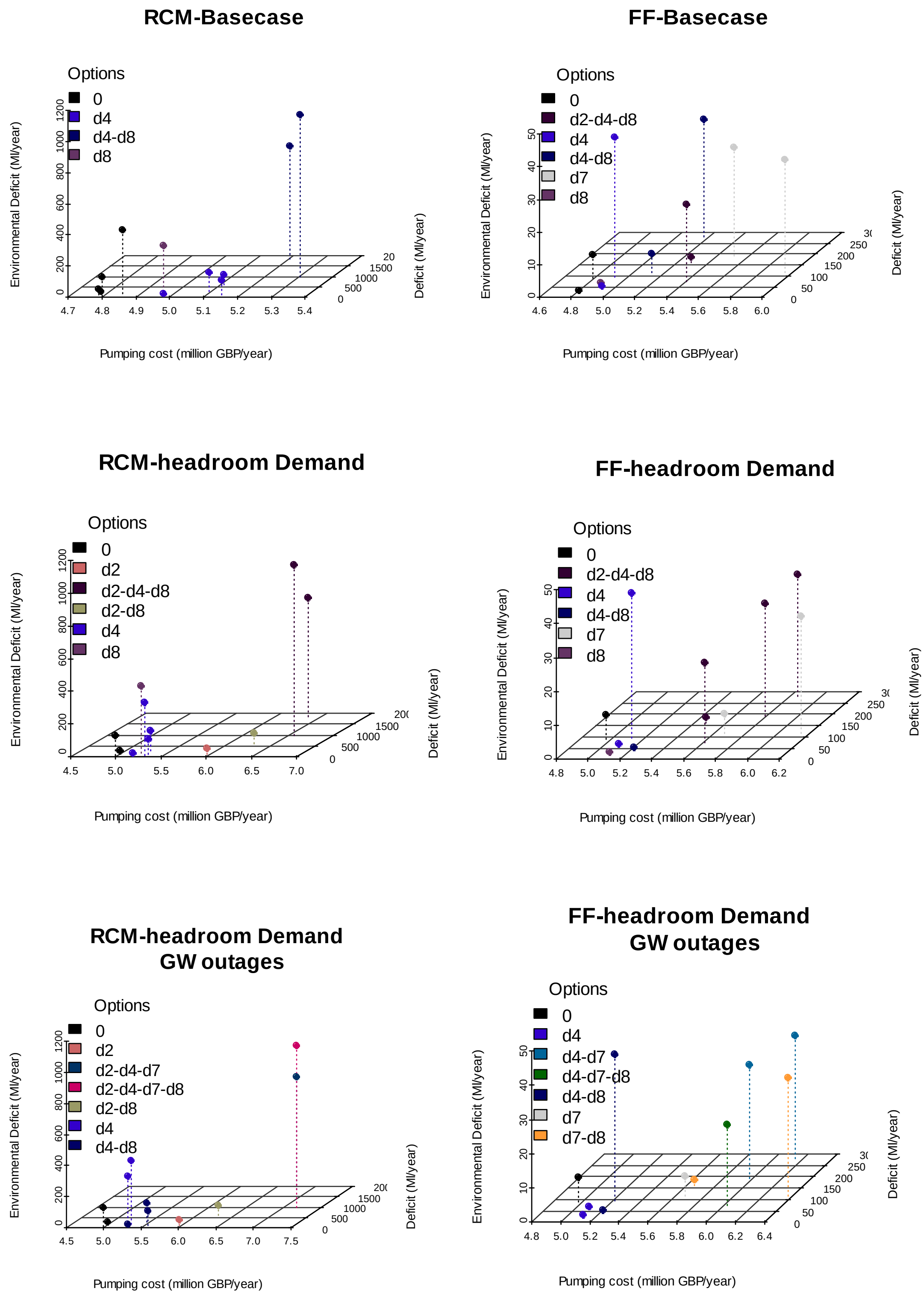


Figure 8.9 Comparison of option preference under the climate conditions of the RCM and the FF product for the 2030s

Moving on to the 2050s, the picture becomes more complex as there are additionally four socio-economic scenarios. There are improvements in the water demand level under Innovation and Sustainable Behaviour. Therefore for the Innovation, Local Resilience and Sustainable Behaviour scenario, the composition of selected option portfolio remains similar or with slightly less options compared to that of the 2020s and 2030s, the Market Forces scenario requires a significant amount of strategies to adapt.

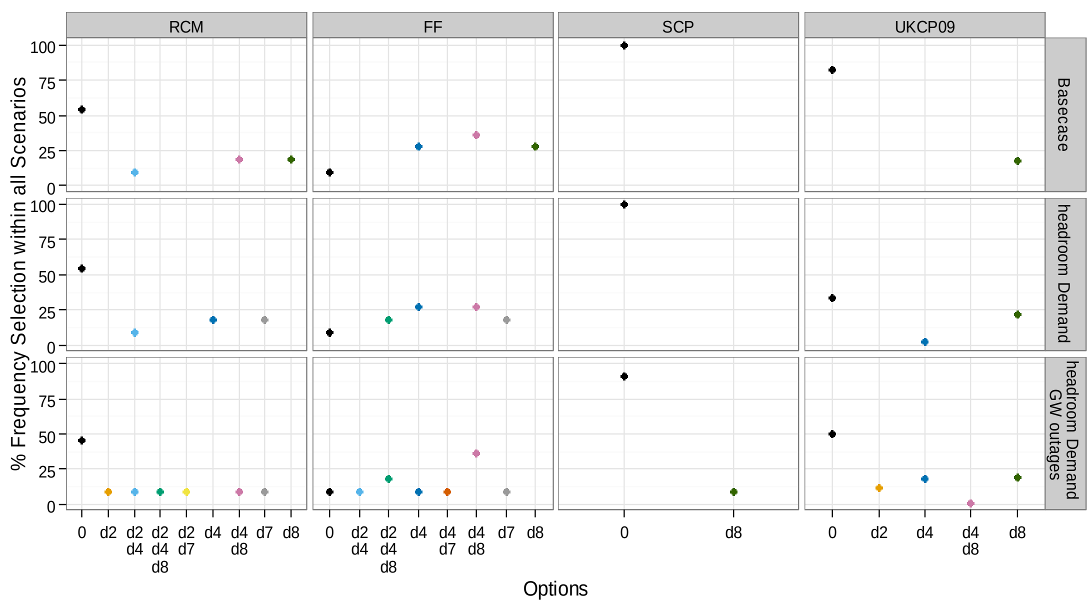


Figure 8.10 Frequency graph of the option portfolio in 2050s under the Innovation socio-economic scenario

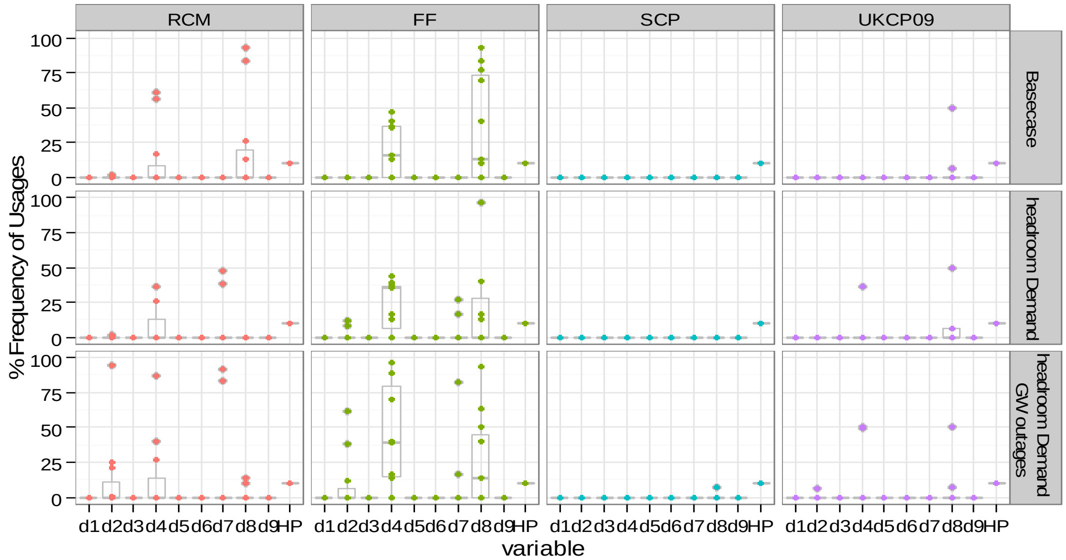


Figure 8.11 Option usage frequency under 2050s Innovation

Under this demand scenario, the different option selection amongst climate products becomes smaller and the option portfolios often include two to more options. Additionally, under the risk of groundwater outages, option selection of the RCM and UKCP09 conditions further include d3, the transfer augmentation option, as most of the additional supply sources are around the Hardham area and have to pass by the d3 link before being delivered to other zones. This socio-economic demand profile also indicates the increased vulnerability of Worthing and Brighton, when d1 (option for the Brighton area) and d9 (option for the Worthing area) are selected. In the Brighton area, d1 and d6 are both desalination options, with d1 having higher supply capacity. Due to them being implemented on the same site, these two options are mutually exclusive. Yet, the model indicates that d1 is preferred over d6, therefore demonstrates the high need of additional supply on this area.

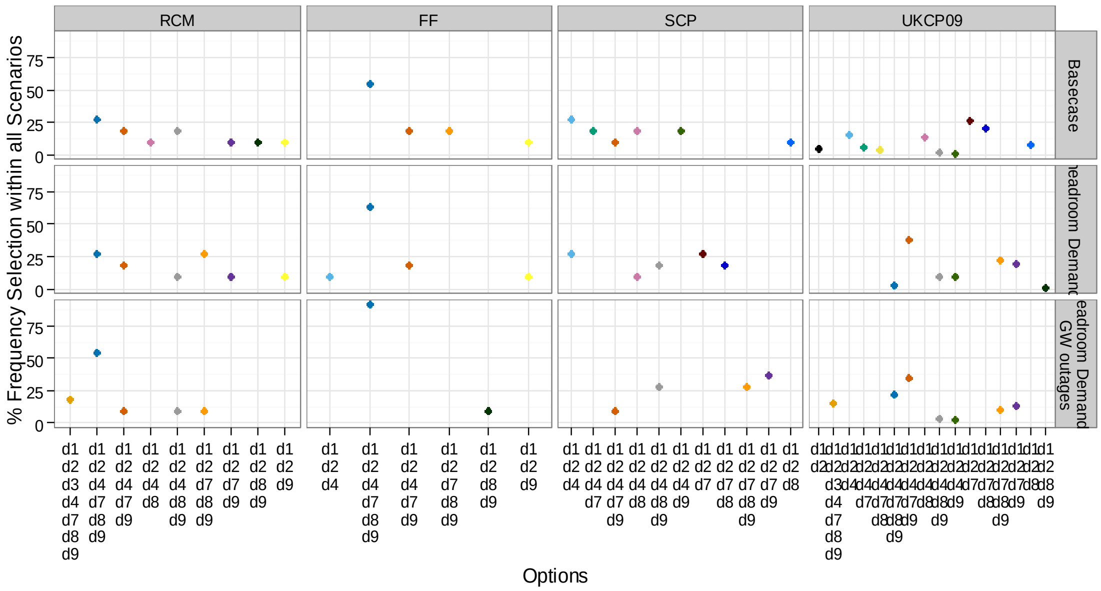


Figure 8.12 Frequency graph of the option portfolio in 2050s under the Market Forces scenario

Figure 8.13 further shows the usage of each option in the area. Under all scenarios, universal metering becomes an essential strategy with 100% usage rate, followed by the desalination plant in Brighton. d4 (Arun Abstraction), d7 (Ford Effluent Reuse) and d8 (Wellfield Optimisation) also appear to be vital to increase the coping capacity.

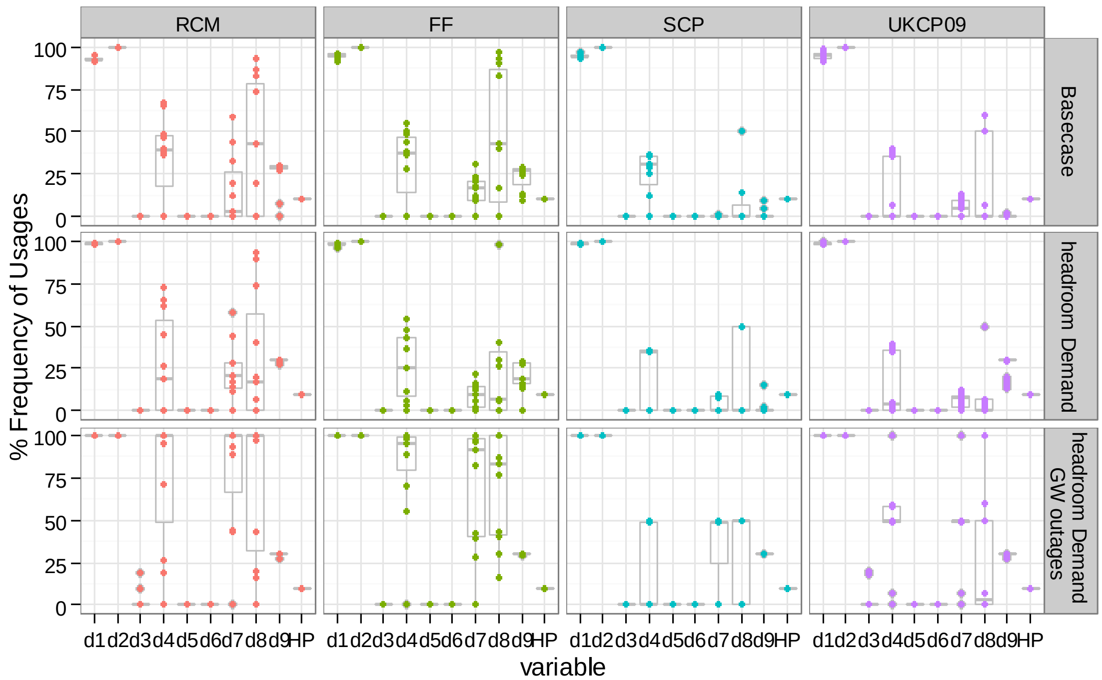


Figure 8.13 Option usage frequency under 2050s Market Forces

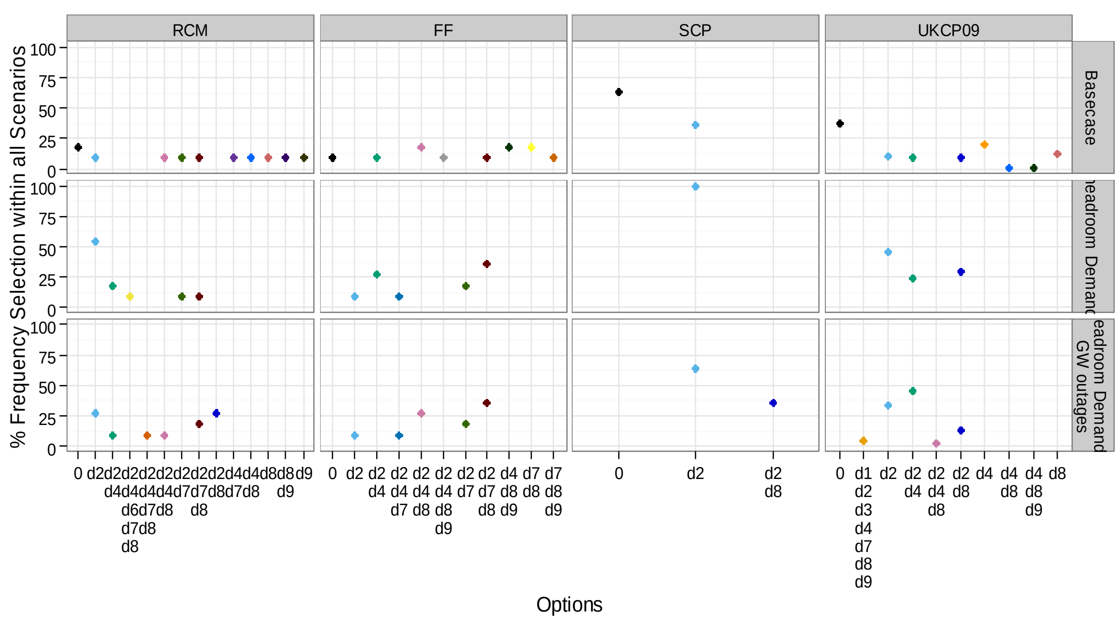


Figure 8.14 Frequency graph of the option portfolio in 2050s under the Local Resilience scenario

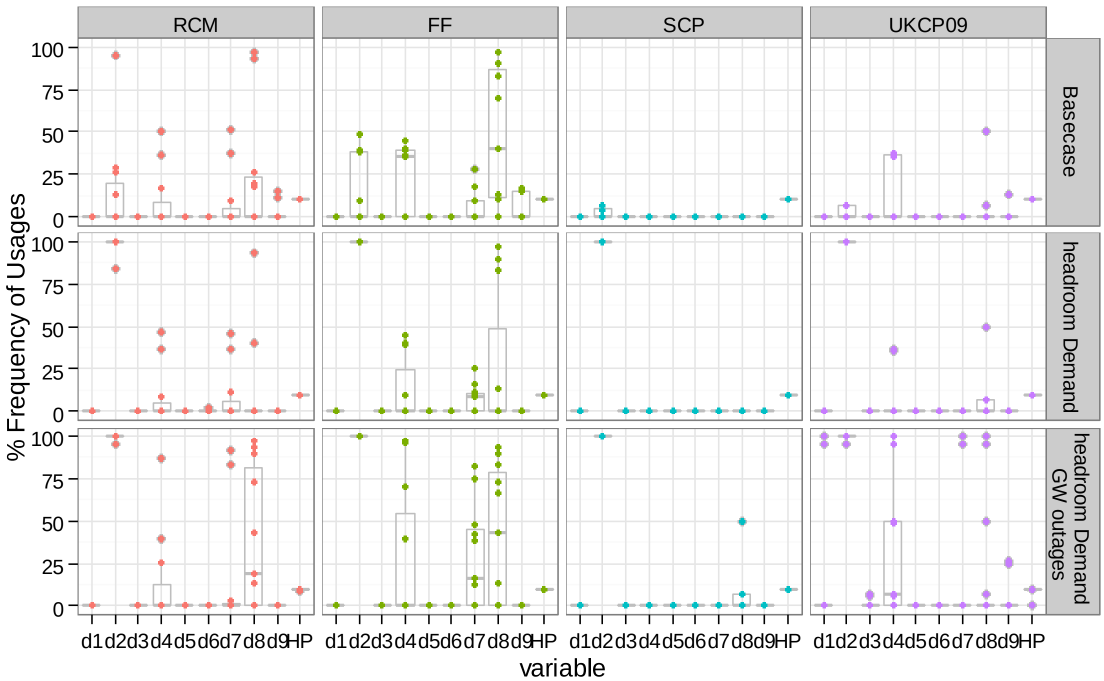


Figure 8.15 Option usage frequency under 2050s Local Resilience

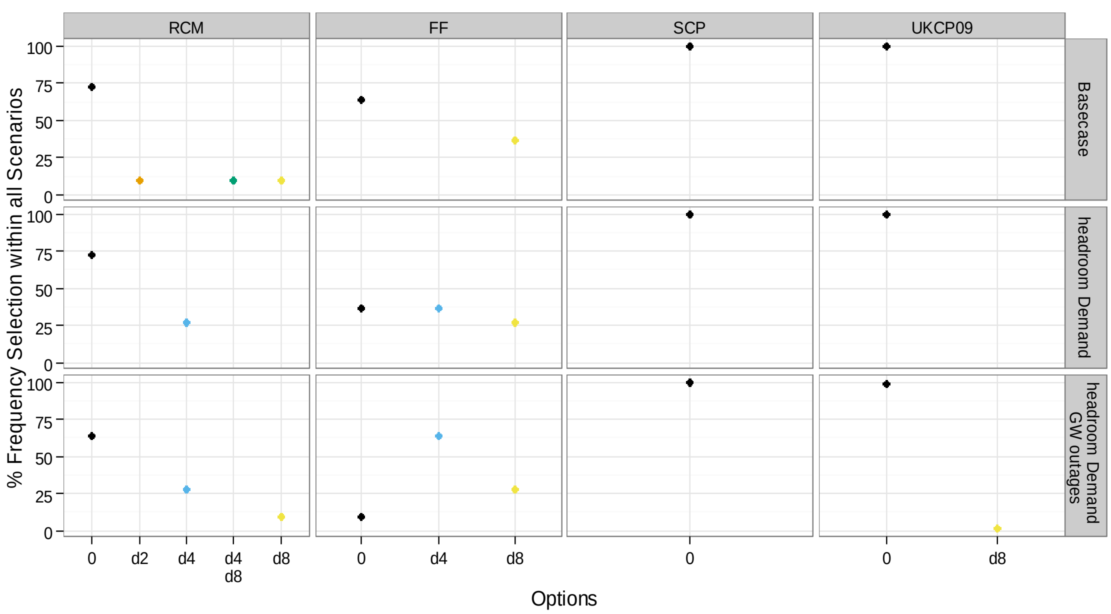


Figure 8.16 Frequency graph of the option portfolio in 2050s under the Sustainable Behaviour scenario

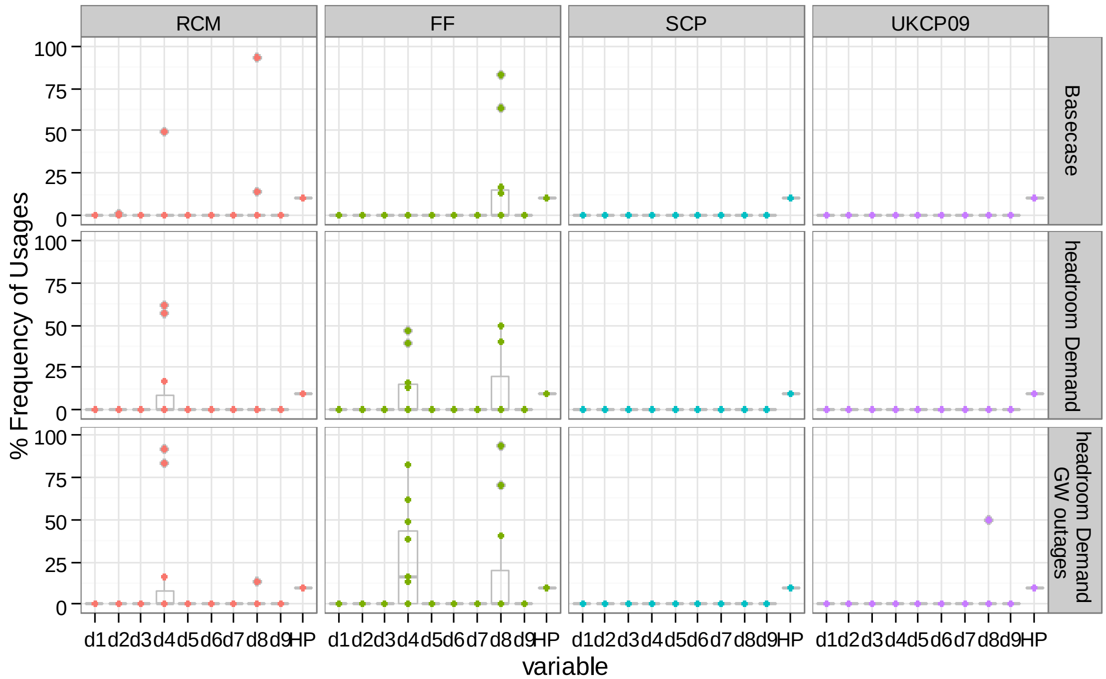


Figure 8.17 Option usage frequency under 2050s Sustainable Behaviour

Regarding the decision sensitive conditions from the 2020s to the 2050s, they appear to be consistent within each climate product Figure 8.18 and 8.19 compares the preferential structure of option selections for the 2030s and the 2050s Market Forces scenarios. As can be seen, since the Market Forces scenarios is much more severe than the 2020s and the 2030s scenarios, option selection moves toward options of more capacity but with higher cost. Nevertheless, this trade-off between cost and performance could not help bring supply deficit back to the level of the 2020s or the 2030s. While operational costs of the 2030s are generally within the region of 4 to 5 million GBP per year, those of the 2050s Market Forces jumped to the region of 5 to 15 million GBP per year and with supply deficit from 0 to 1100 Ml/year.

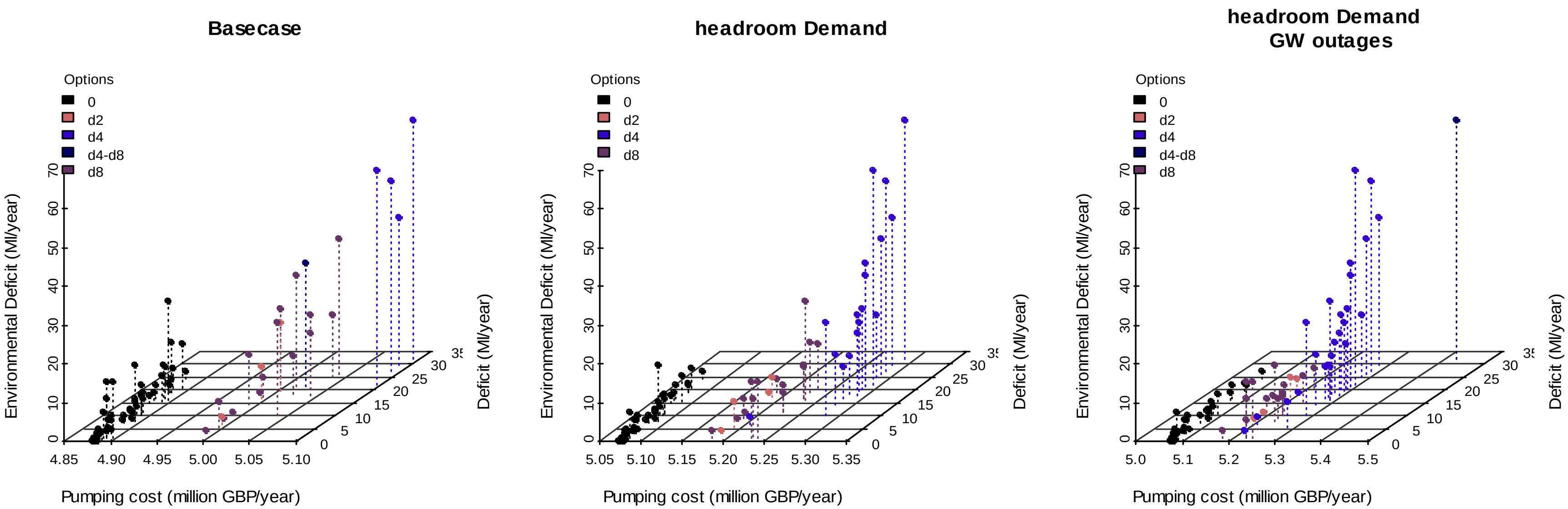


Figure 8.18 3D plot of Environmental Deficit versus Pumping Cost and Supply-Demand Deficit in 2030s for the UKCP09 product

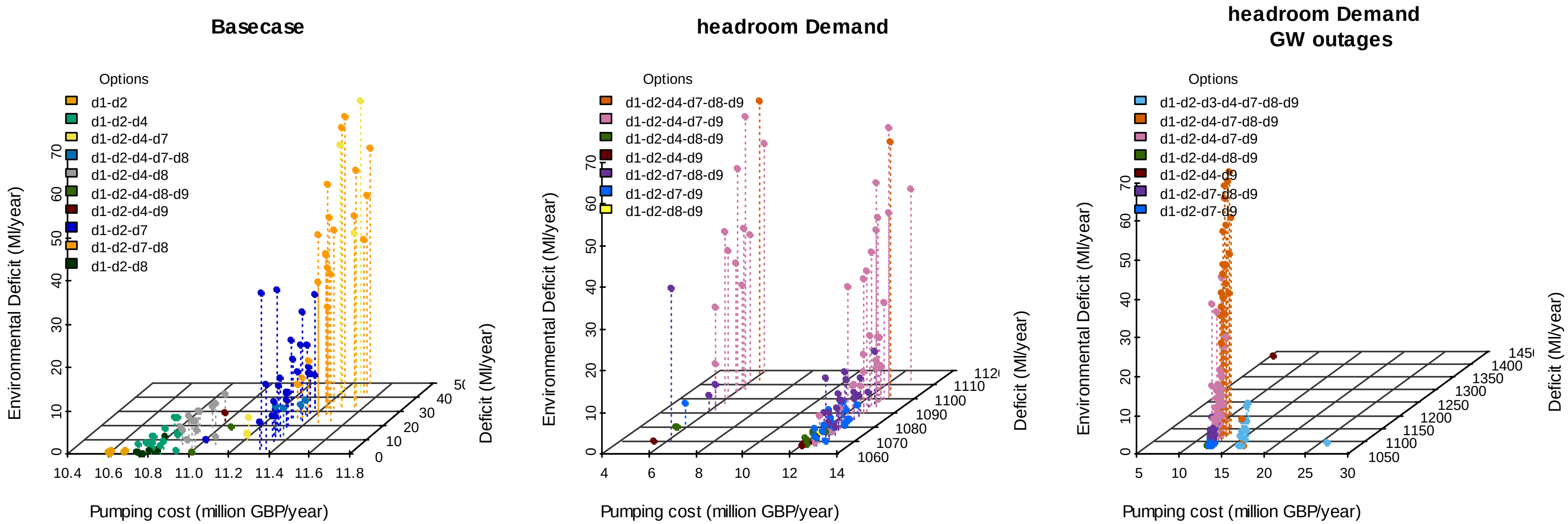


Figure 8.19 3D plot of Environmental Deficit versus Pumping Cost and Supply-Demand Deficit in 2050s Market Forces for the UKCP09 product

8.3.2. Deficit Analysis

As the 2050s scenarios demonstrate a wide range of option portfolios, these portfolios are driven by both demand and the climate scenarios. Overall, the most severe demand and the extra risks of groundwater outage often necessitate the implementation of additional supply sources. However, when demand grows by 35% from the 2007 demand, universal metering becomes a key option. The analysis therefore shows that the higher the demand level is, the more essential metering and demand management become. In practice, this is also likely to be a vital factor, as metering can provide additional information on the demand pattern and any potential interactions with climate conditions. In general, the available management strategies of the water resources system assist the system with adaptation to changes in climate and water demand. This section further analyses the location of the remaining deficits and network attributes to identify the remaining vulnerability of the area. Figure 8.20 to Figure 8.25 demonstrate that except for the 2050s Market Forces scenario, most of the deficits in other time slices and demand scenarios occur in South East Water (SEW) transfer and the environmental flows.

The persistence of the deficits in these locations can be explained by the distribution of the planning options and network distribution. Firstly, MRF Weirwood and Rother are the environmental residual flows of the Medway and the Rother. Therefore, except for the d5 (which was not implemented since it does not help increase the system coping capacity; it instead only reduces the requirement of the environmental flows), no other option can alter the deficits in these nodes. On the other hand, the deficit in SEW is due to network attribute and option location. As can be seen in Figure 8.1, the cluster of SEW, Weirwood Reservoir and the environmental node Minimal Residual Flow for Weirwood (MRFWW) feeds water into the Buchan Hills and Turner Hills node but do not receive supply from the rest of the Sussex network. Yet, most supply options are located around the River Rother and Hardham, which feed water into the Sussex nodes and at maximum 105 Ml/d to the Worthing area. Therefore, none of these options can reduce the deficit in SEW, which often occurs when the reservoir experiences a long succession of low flows which cause deficits in the environmental flows and restrict Weirwood capacity to supply water for the transfer to South East Water.

While this deficit does not pose risks to the Sussex area, the risk of transfer failure under climate change should be considered between South East Water and Southern Water. Furthermore, it poses a question on the reliability of inter-company transfer, such as the link from Portsmouth Water to Southern Water's Sussex North. In the optimisation model, this source has been assumed to be perfectly reliable. However, in practice, the inter-regional supply capacity often depends on the temporal and spatial spread of droughts. As Rahiz and New (2013) has shown, droughts in the South East could spread across the whole southeast England area. Water shortage risk therefore needs to be further considered in other regional study.

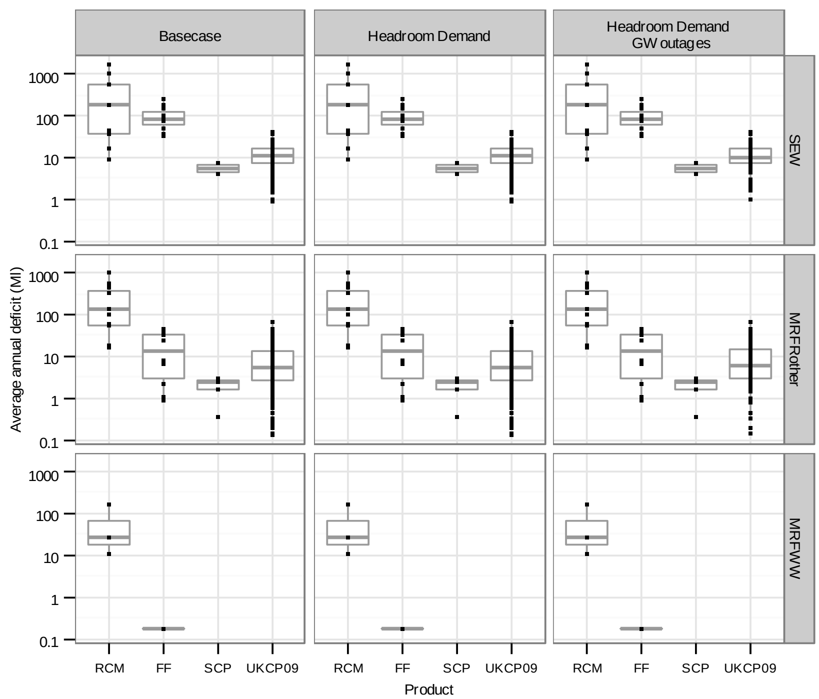


Figure 8.20 Deficit locations in 2020s

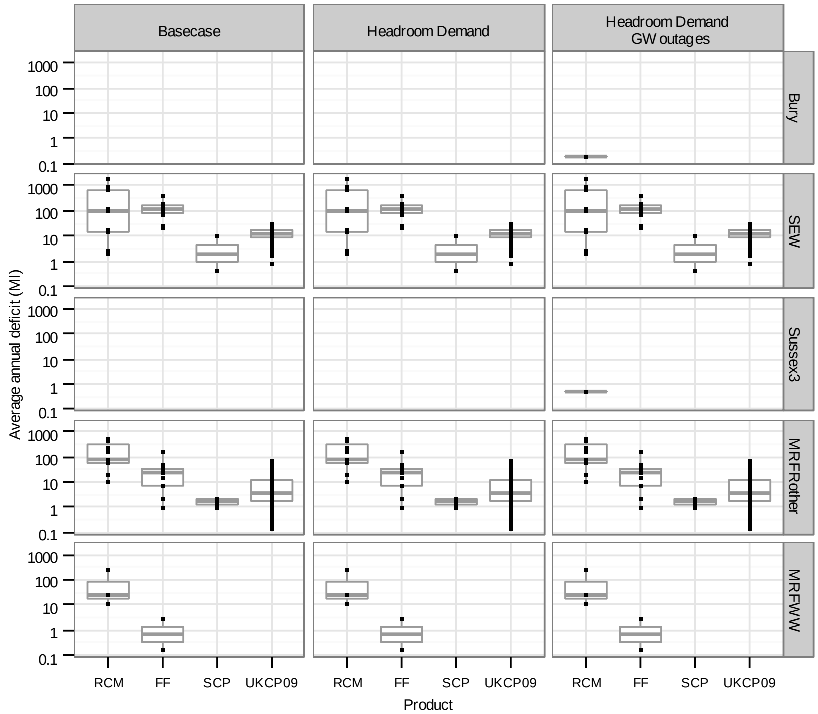


Figure 8.21 Deficit locations in 2030s

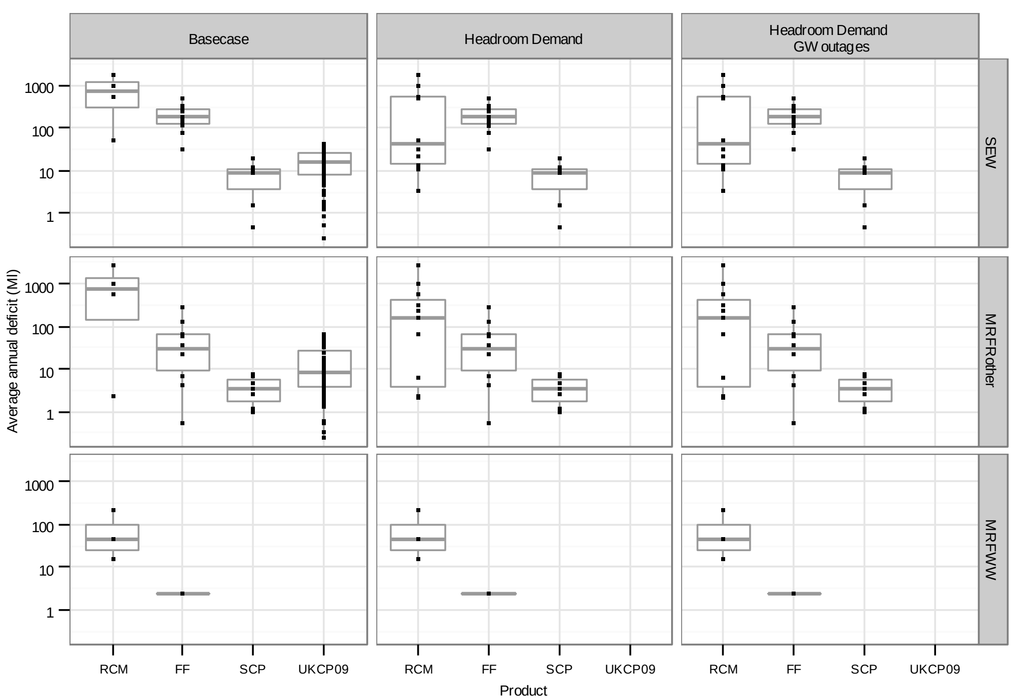


Figure 8.22 Deficit locations in 2050s Innovation

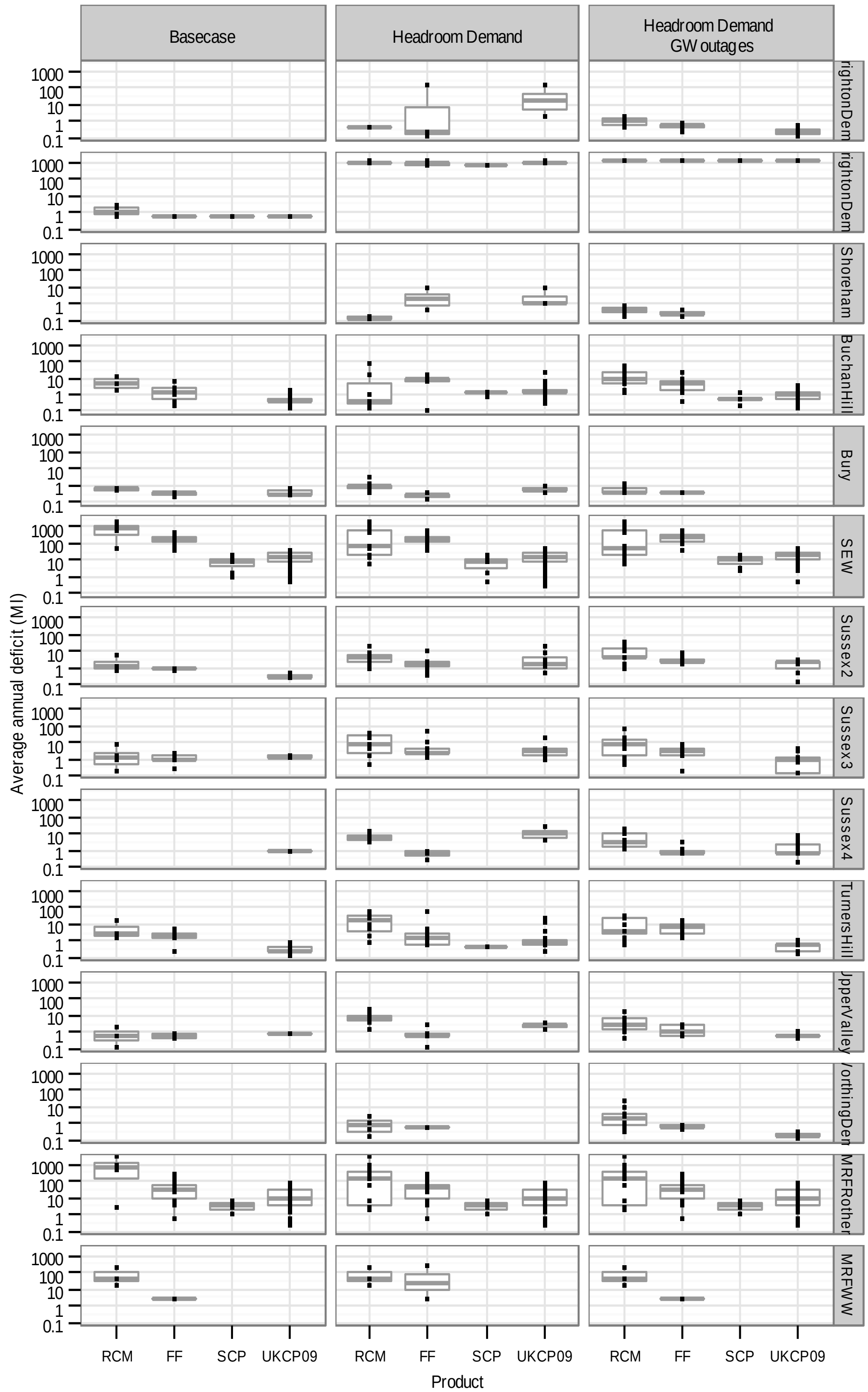


Figure 8.23 Deficit locations in 2050s Market Forces

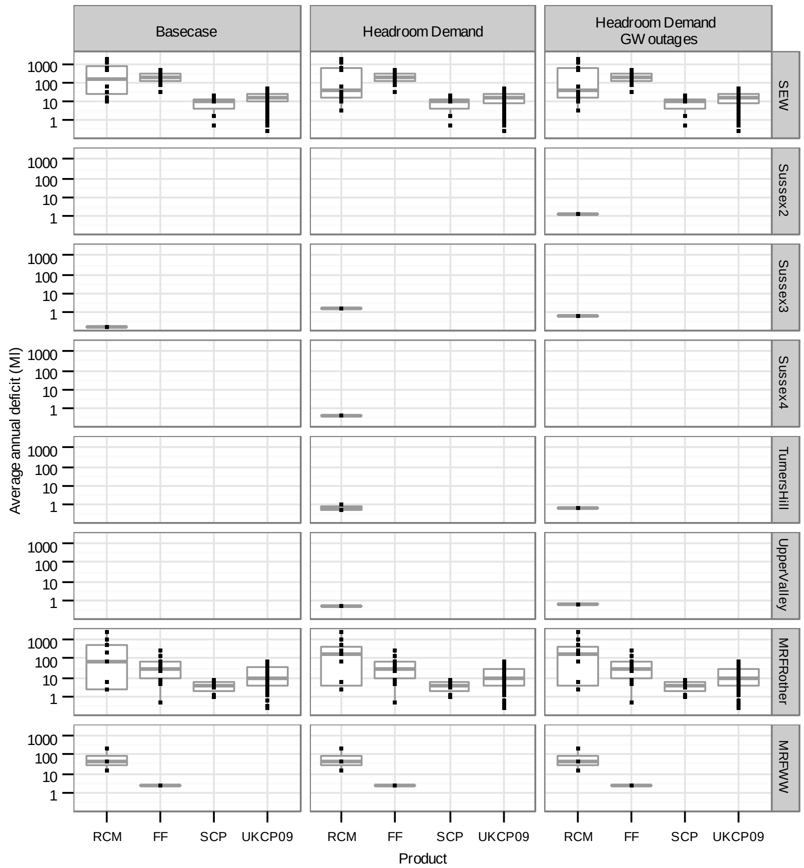


Figure 8.24 Deficit locations in 2050s Local Resilience

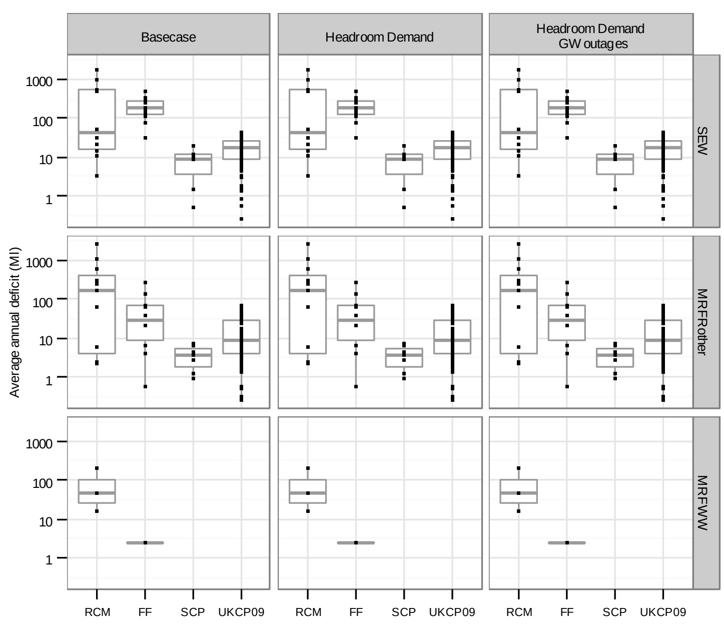


Figure 8.25 Deficit locations in 2050s Sustainable Behaviour

8.3.3. Robust Options Analysis

The previous section has shown the groups of optimal strategies under optimization. Without this pre-selection process, the number of all option portfolios to be considered would be $2^9=512$; using the optimization model reduces the potential candidates to 39 distinct sets. However, as the Optimisation model only displays one Pareto optimal strategy for each scenario, it could not compare the performance of that optimal strategy against other sub-optimal strategies. For instance, Option A is optimal for Scenario 1 and Option B is optimal for Scenario 2; however, the Optimisation model does not give any comparison of Option A versus Option B in both Scenario 1 and 2. To overcome this limitation and achieve a robust option that works well under all scenarios, this section used the simulation model to analyse the performance of all the options that the Optimisation Model has selected. Moreover, this analysis will further test option performance under imperfect information, as supply operation is now rule-based instead of being optimized based on perfect knowledge of climate and demand information.

Under imperfect information and rule-based operation, the Sussex system is much less robust to climate and demand risks. In particular, the Optimisation Model could successfully cope with the 2020s water demand without the need of any additional option (Figure 8.26). Meanwhile the Simulation Model indicates the need of extra measures. Amongst the portfolios, d4 (Arun Abstraction), d7 (Ford Effluent Reuse), d4-d8 (combination of Arun Abstraction and Wellfield Optimisation), or d2-d4-d8 (set d4-d8 and demand management via universally metering) are the most effective strategies to reduce supply deficit. While the operational cost of d4, d7 or d4-d8 is similar, the cost of the d2-d4-d8 is significantly higher due to the implementation of demand meters (**Figure 8.27**).

The results further show that the performance rank of the strategies remains quite consistent under different climate products. This is the case even for the unbias-corrected RCM projections. Thus while the absolute supply deficit vary across scenarios, the decision makers can expect that the combined strategy of d2-d4-d8 or the single option d7 will be amongst the most effective measures.

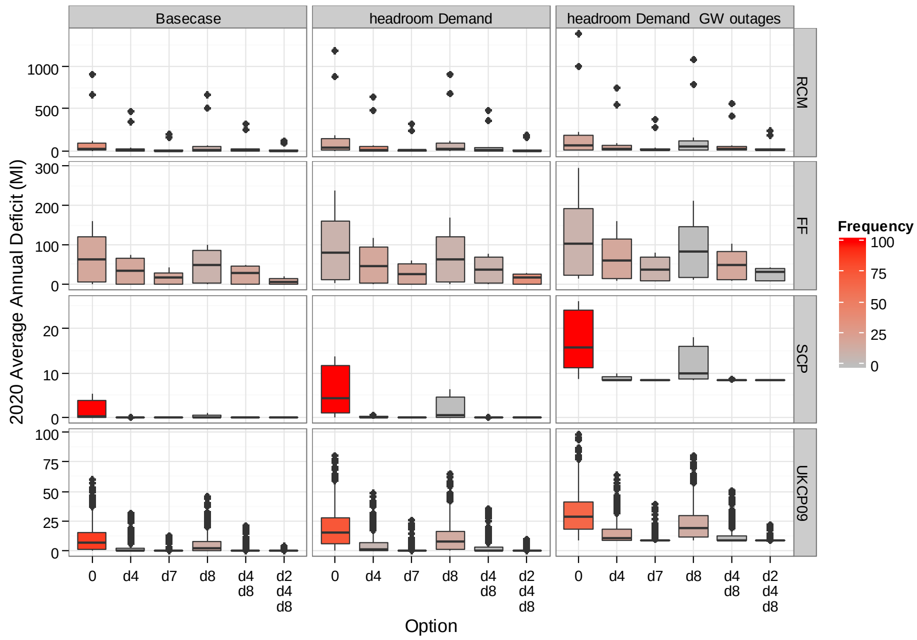


Figure 8.26 Average annual supply deficit in the 2020s. The % Frequency colour gradient shows how often the option was selected in the Optimisation Model, such that the option in red was the dominant option of the Optimisation Model.

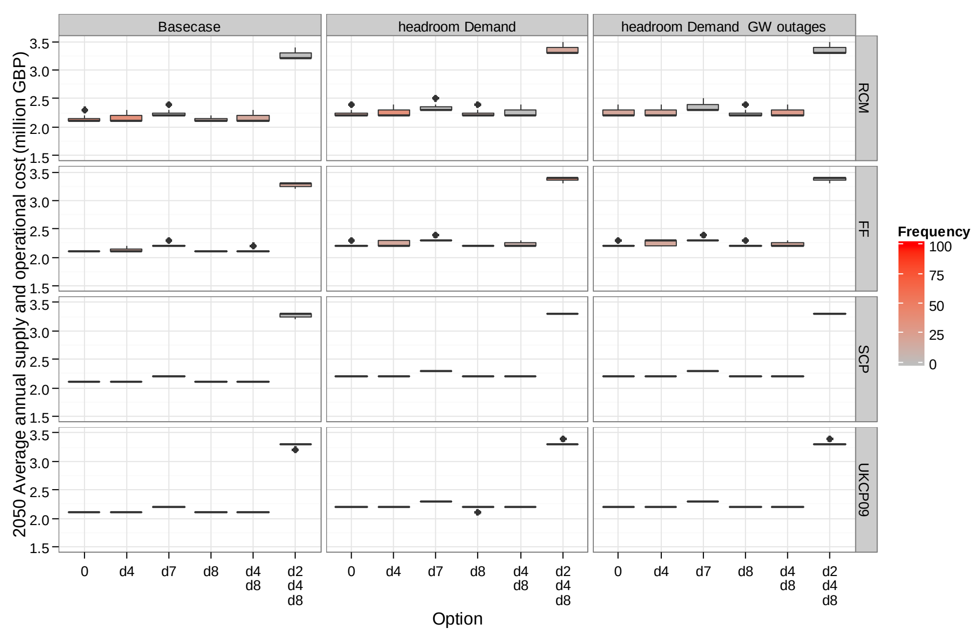


Figure 8.27 Average annual supply cost in the 2020s. The % Frequency colour gradient shows how often the option was selected in the Optimisation Model, such that the option in red was the dominant option of the Optimisation Model.

In other words, the post-processing uncertainty in climate projections is a significant uncertainty factor in determining the climate change impacts; however, in terms of decision making, this uncertainty do not play a major role and the preferential ranking of the options is still preserved. While both have similar mean effect, effect variation (represented by the span of the box plot) of the former is smaller than that of the latter; yet, d2-d4-d8 is significantly more expensive to implement and operate than d7.

Overall, the Simulation Model indicates that all the measures could restrict supply deficit to under 150 Ml/year; however the particular selection will be dependent on the financial budget and the risk averseness level of the decision maker. The results also highlight the impacts of scenario variation to option selection. Under the time series-based RCM and FF products, the selected optimal options vary in response to the decision sensitive conditions and the dryness of the scenario. Meanwhile, the Change Factor-based SCP and UKCP09 have a strong dominant option for 2020s and 2030s. However, the dominance of the inaction strategy (0) under the SCP and UKCP09 product could also be due to their relatively less severe climate conditions, compared to the RCM and FF products.

Considering the 2030s, the situation and the options remain similar to those of the 2020s. d7 and the portfolio d2-d4-d8 are still the best performing and least varying strategies (Figure 8.28). Again, the adaptation choice depends on the decision maker's preference on the operational and investment cost, as well as the supply safety margin of the option. However, the need to adapt is not yet pressing, and in various scenarios, the system can still supply sufficiently deficit using the existing sources.

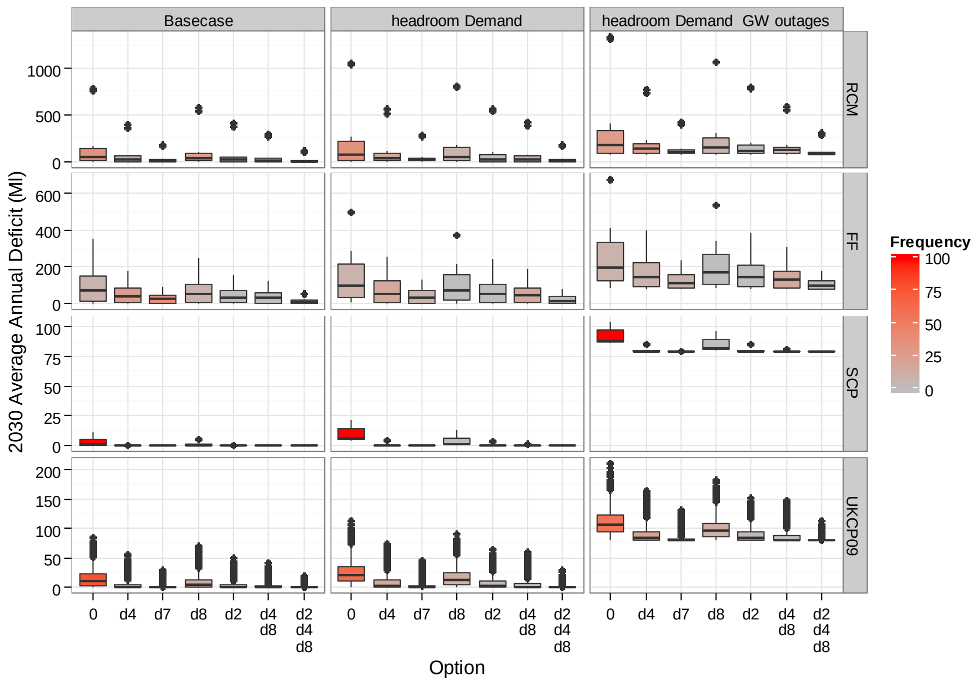


Figure 8.28 Average annual supply deficit in the 2030s. The % Frequency colour gradient shows how often the option was selected in the Optimisation Model, such that the option in red was the dominant option of the Optimisation Model.

Moving to the 2050s, the adaptation strategies become much more difficult as beside the climate factor, demand uncertainty also becomes a major controlling factor. Under the mild demand change scenarios of Innovation (Figure 8.29) and Sustainable Behaviour (Figure 9.30), there is no need to implement more than the strategies identified for the 2020s and the 2030s. The system is highly dependent on groundwater supply and therefore extremely sensitive to groundwater outages. Supply deficit does not change significantly under the headroom demand, which is 5% higher than the baseline demand. This phenomenon thus shows that the system has sufficient capacity to cope with this demand deviation. However, when demand growth is coupled with groundwater unreliability, annual supply deficit risks shift upward by approximately 500 Ml in the Innovation scenario. (Figure 8.28) while remaining unchanged in the Sustainable Behaviour (Figure 8.29). As such, while both of these socio-economic scenarios are of water shortage risk, the Sustainable Behaviour scenario is more resilient and robust to additional pressure from groundwater outages.

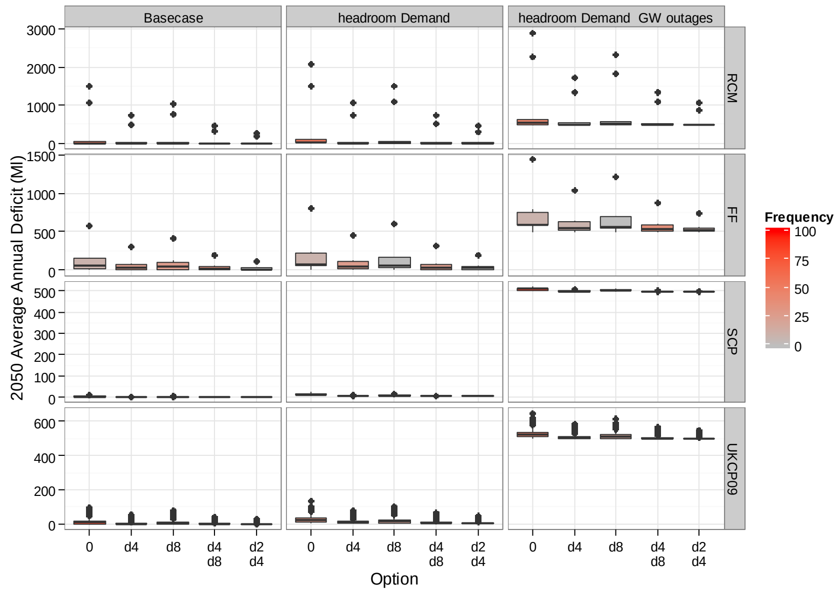


Figure 8.29 Average annual supply deficit in the 2050s under the Innovation socio-economic scenario. The % Frequency colour gradient shows how often the option was selected in the Optimisation Model, such that the option in red was the dominant option of the Optimisation Model.

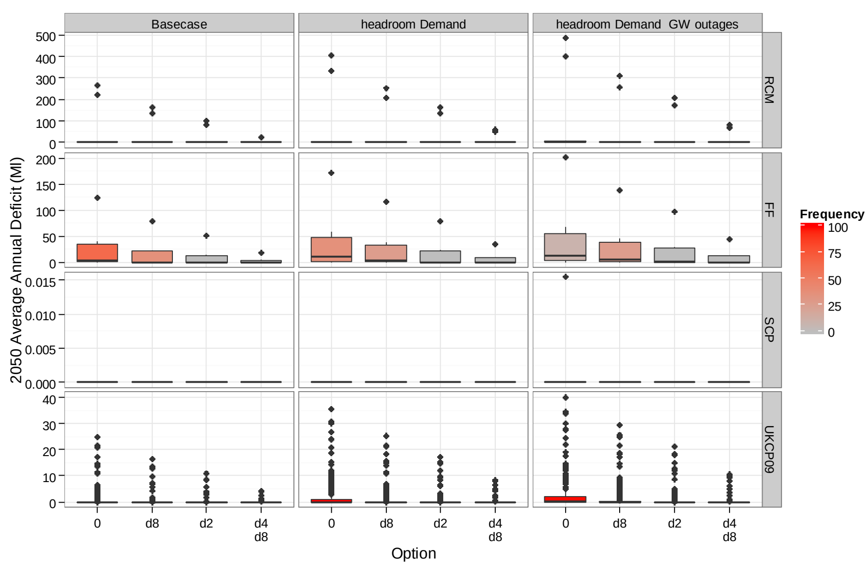


Figure 8.30 Average annual supply deficit in the 2050s under the Sustainable Behaviour socio-economic scenario. The % Frequency colour gradient shows how often the option was selected in the Optimisation Model, such that the option in red was the dominant option of the Optimisation Model.

Under the more severe 2050s Local Resilience scenario, supply deficit further increases Figure 8.31). As demand growth becomes a more dominant uncertainty factor, the differences due to using different climate products diminish. In essence, RCM, FF, SCP and UKCP09 all show similar supply deficit levels under the baseline demand, headroom demand and additional groundwater outage risks. Yet the supply deficit is quite high (4000 Ml/year ~11 Ml/day shortage) and thus shows that all the available options are not sufficient to reduce the water supply deficit. As Section 8.3.2 has demonstrated that these deficits mainly occur in the South East Water transfer, there exists a need to identify options that can reduce the deficit, such as changing the reservoir control curve, transferring water from the other part of the network to this area, build new supply sources or renegotiate with South East Water regarding the transfer agreement.

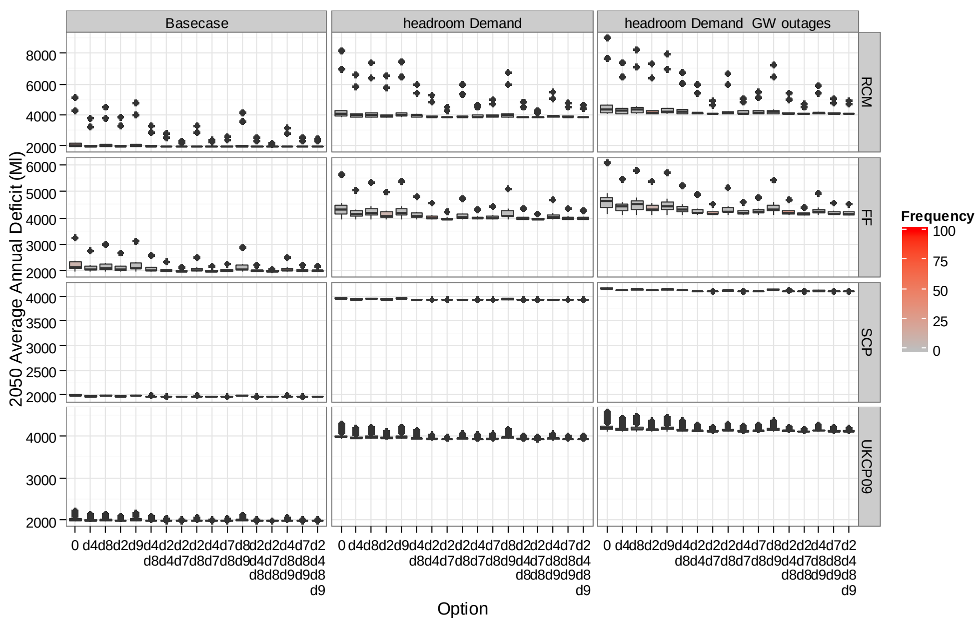


Figure 8.31 Average annual supply deficit in the 2050s under the Local Resilience socio-economic scenario. The % Frequency colour gradient shows how often the option was selected in the Optimisation Model, such that the option in red was the dominant option of the Optimisation Model.

The socio-economic trend of Market Forces will pose significant risks of failures to the Sussex system. As the Optimisation Model has demonstrated, heavy investment-high impact options such as the desalination plant in the Brighton area and universal metering in the whole area become necessary. Under the 2050 Market Forces scenarios, the single options are not adequate to abate supply shortages; consequently all the selected sets contain at least two options (Figure 8.32). While offering more coping capacity to drought risks, the combined options are often expensive and the operation cost of the system increases with the addition of each option (Figure 8.33). Under a 5% increase from the baseline demand, the overall supply deficit increases; however when groundwater supply reduces, the system suffers less deficit shortages overall; however analysis on each water resource area shows that this reduction is due to a smaller overall deficit in Worthing and Brighton; however, the failure frequencies increase in all of these areas. Furthermore, while total deficit reduces in Worthing and Brighton, groundwater outages lead to higher supply deficit and supply failure frequency in Sussex North. While there is a close link between magnitude and frequency of failures, these changes show that groundwater outage risks affect not only the magnitude of failures but also their frequency; furthermore, they show that the level of risks can change differently in each resource area in response to the same risk factor. Under the same socio-economic scenario, optimised planning options selected for the RCM and the FF products often have higher supply capacity, added by demand reduction via metering. This is because the RCM and the FF products project a higher level of water shortage due to the diminishing of surface flows in River Rother and River Medway (which feeds the Weirwood Reservoir).

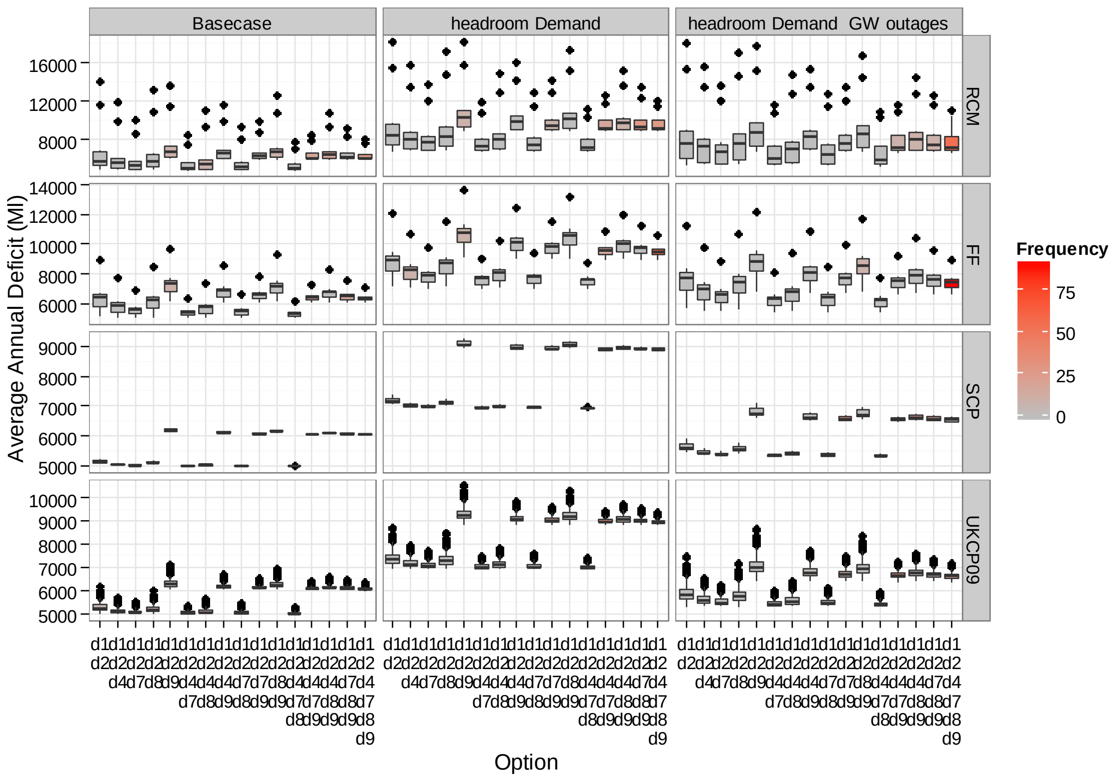


Figure 8.32 Average annual supply deficit in the 2050s under the Market Forces socio-economic scenario. The % Frequency colour gradient shows how often the option was selected in the Optimisation Model, such that the option in red was the dominant option of the Optimisation Model.

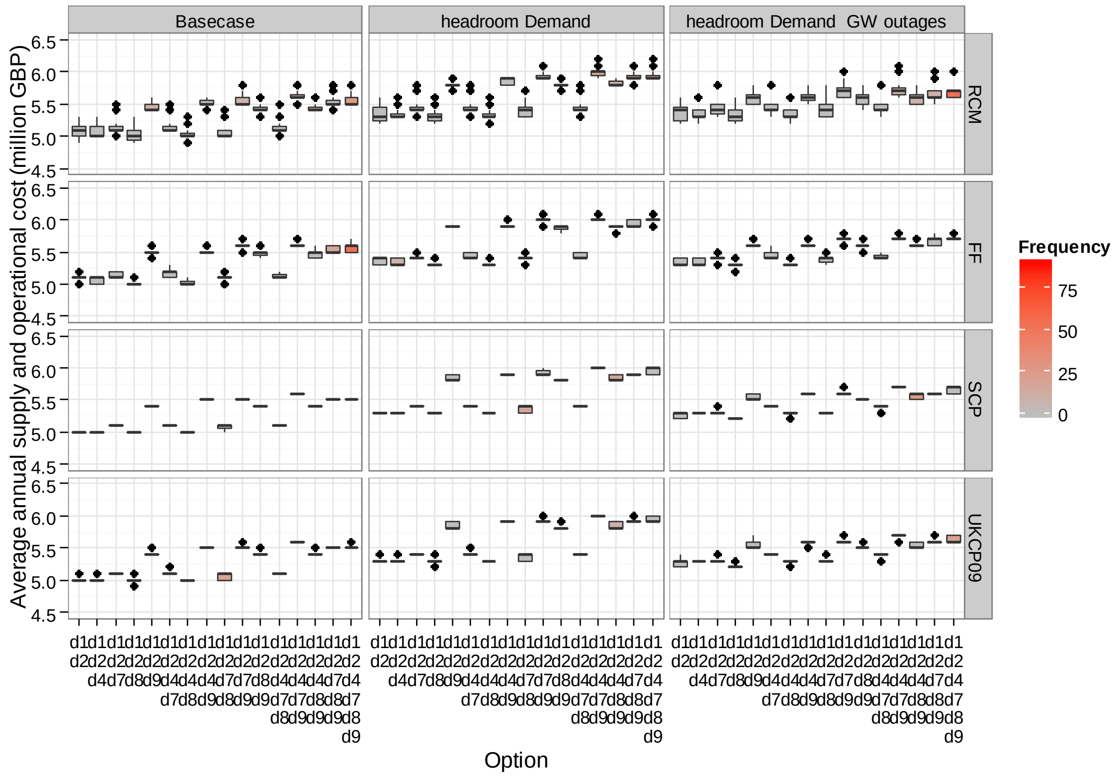


Figure 8.33 Average annual supply cost in the 2050s under the Market Forces socio-economic scenario. The % Frequency colour gradient shows how often the option was selected in the Optimisation Model, such that the option in red was the dominant option of the Optimisation Model.

8.4.CONCLUSION

In conclusion, this chapter has further analysed the options available to the study area and the remaining system vulnerability. The chapter shows that indeed using different climate products can lead to different optimal adaptation needs and plans. In essence, under the mild SCP climate projections, the area does not need any adaptation strategies until 2050s when adaptation strategies will be driven by the actual demand growth. On the other hand, the RCM and FF projections indicate an early need of adaptation since the 2020s and an increasingly need for utilising the options in 2050s. The UKCP09 product, which has been post-processed to include a wider range of uncertainty, does not indicate a significantly higher need of adaptation. Indeed, the system appears to be robust under the SCP and UKCP09 conditions and with little need of additional supply or demand measure. Yet, the system is much less robust under FF and RCM and needs the assistance of at least universal demand metering, Arun abstraction or Ford effluent reuse. The 2020s and 2030s are still dominated by climate uncertainty, with options selected mainly due to the different climate sources and the projected climate condition in that specific scenario. In the 2050s, such influence interacts and is influenced by demand uncertainty, with demand and climate uncertainty being two major controlling factors in the Innovation, Local Resilience and Sustainable Behaviour scenarios. However, once demand grows past the 35% threshold from the 2007 baseline demand, it becomes the most important factor on system vulnerability and which adaptation strategies to be selected. The extreme demand profile leads to the key role of universal metering, desalination plant in Brighton and the combination of Arun Abstraction, Ford effluent reuse and Wellfield optimisation in the Sussex North area. For certain ensembles of the RCM and FF products, as well as certain scenarios of the UKCP09 product, additional measures such as transfer augmentation and aquifer storage and recovery in Worthing are also indicated.

Yet, the simulation model depicts a much more fragile and responsive water resource system. In order to reduce supply deficit, the decision maker will need to consider Arun Abstraction, Ford Effluent Reuse or a combination of Arun Abstraction, Wellfield Optimisation and optimal demand metering. As these choices perform quite similarly in the 2020s and the 2030s, the choice depends on the preference of the decision makers, such as the preferred safety margin and the financial budget. Nevertheless, the performance ranks of the options do not change even if different climate products are used. Even with the un-bias corrected RCM projections, the ranking is quite similar to the much more processed UKCP09. It thus shows that while climate uncertainty dominates the uncertainty space, an effective adaptation decision may largely reflect the local vulnerability rather than explicitly relying on the climate products. Yet, the more robust decisions are, the higher the operation and investment cost. Since the climate product is essential to determine the level of supply deficit, it is essential for selecting which level of robustness the decision makers should aim for.

Overall, the sets of options are sufficient to reduce the area's vulnerability under optimization but not under simulation. The remaining deficits in transferring to South East Water and in fulfilling the environmental flow requirements are inherent to the Sussex delivery network attributes. In particular, there is no option that can influence environmental flows, and the location of the transferring SEW node does not allow for receiving water supply from other parts of the network. While this SEW deficit does not pose direct risks to the Sussex network, it indicates that Southern Water and South East Water need to revise their transfer agreement in view of future climate risks. Besides, it also demonstrates that inter-regional transfers may not be as robust as assumed. In this study, the Portsmouth transfer was assumed to be perfectly reliable; however, its reliability in practice is dependent on the drought extent and the supplying capacity of Portsmouth water under droughts. Therefore, the study indicates a need for future research on inter-regional drought risks and water operation.

Chapter 9. ROBUST ADAPTATION PATHWAY ANALYSIS- A DISCUSSION

9.1.REVISITING ROBUSTNESS IN THE SUSSEX CONTEXT

9.1.1. Comparison of the robustness frameworks

The previous chapters have demonstrated the cascade of uncertainty from climate change information to the water resource planning stage. Overall, climate post-processing and demand scenarios are two controlling uncertainty factors of the water supply deficit level; however, the location and the level of system vulnerability are determined by the attributes of the water delivery network and the available options. This section revisits the concepts and frameworks of robustness as discussed in Chapter 2; based on the results of the previous chapters, it analyses these aspects of robustness in the context of the Sussex water resource system. It focuses on option robustness and system robustness, which emphasise the coping range of an option versus the overall system.

As reviewed in Chapter 2, robustness approaches in water resource planning includes robust optimisation, real option analysis, info-gap decision theory and robust decision making. Overall, they deviate from the traditional model of relying on a single scenario or distribution of outcomes. Furthermore, they emphasize the multi-source and multi-impact nature of uncertainty. Classical engineering and statistical robustness aims to maximize the possibility of the chosen option being the optimal strategy under imperfect information. Another robustness measure, the crisp set approach (Rosenhead et al., 1972), meanwhile considers the number of pathways before and after implementing a decision. As such, an option that strengthen the supplying capacity of the system but rules out the implementation of other strategies is considered robust by the engineering approach but not so by the crisp set approach.

Both of these aspects are relevant to adaptation decisions as such decisions should cope with the present risks but also accommodate potential system transitions in the face of uncertainty and future risks. As a combined extension of these approaches, the Real Option approach considers the whole adaptation process as a decision tree from which decision makers can consider trade-offs between the least-cost pathways versus the flexibility to adapt. Meanwhile, the Info-gap Decision Theory and the Robust Decision Making approaches focus on the uncertainty element. The former looks at possible levels of deviation from the 'best estimates', in this case the projections of climate conditions and water demand level, and gauge the option performance against its working uncertainty zone (Korteling et al., 2013). For instance under perfect information, option A is the optimal least-cost option; however its performance quickly deteriorates if demand increases by 5%; meanwhile a suboptimal option B could continue maintaining its performance up to a demand grow by 10%. Under the Info-gap approach, option B would be identified as a robust option instead of the option A.

Finally, the Robust Decision Making approach is distinctive compared to other approaches due to its emphasis on vulnerability assessment. Similar to the Info-Gap Decision Theory Approach, it considers the effectiveness of options under deep uncertainty in the form of different scenarios. In particular, the decision makers can state a performance threshold level above which the system is considered to be vulnerable and the options ineffective. Additional options or alternatives are then identified and assessed toward the goal of obtaining a satisfactory level of system performance. For example, the decision makers may want their water system to have no system failure under 80% of the scenarios; nevertheless under the current system, 30% of the scenarios experience system failure. The analysis then focuses on these 30% of scenarios and identifies strategies that can reduce failures to a 20% level.

Within the context of the Sussex case study, certain aspects of these robustness approaches have been implemented in the analysis. The study combines the Robust Optimisation approach and the Robust Decision Making approach to identify both the optimal and the satisficing options. Moreover such a hybrid approach would help reduce the number of option combinations (2^9 =512) to be considered in the Robust

Decision Making step. The Optimisation process (Chapter 8) has produced a set of 39 option portfolios for Robust Decision Analysis. Also, instead of iteratively consulting the decision makers on their criterion threshold, the model proceeded to compute different criterion values using different option portfolio. As such, the decision makers can be aware of the full range of the option performance, as well as the associated cost. With the classical Robust Decision Making approach, the decision maker focuses on their current preference, with this improvised approach, they can consider changing their preference level.

In terms of constructing the demand and supply scenarios, the approach also enables a partial application of Info-Gap Decision Analysis. Specifically for the 2050s period, the baseline and the headroom Demand (5% increase compared to the baseline) in the four scaling levels of the 2007 demand (namely -4%, 35%, 8% and -15%) can represent deviations from the 2007 demand state and possible option portfolios that work well under these ranges of deviation. Finally, by considering the common options amongst the time periods of 2020s, 2030s and 2050s, the decision makers can consider potential implementation pathways that balance between drought risk reduction and system flexibility. The analysis is thus not restricted by any pre-determined preference of robustness level and can accommodate the decision makers' changes in risk averseness.

9.1.2. Adaptation Robustness Analysis

9.1.2.1.Robustness to climate uncertainty and water resource uncertainty

The challenge of a changing climate is one of the key tests for adaptation decisions. Under deep uncertainty of climate change impacts, the Sussex water resource system has to address potential risks from drier summers and more variability in water supplies. Overall, the Sussex system is relatively robust to the past drought patterns but performs poorly under new drought sequences as projected by the FF ensembles. As such, there is also an uncertainty due to climate products, in this case the different post-processed products of the HadRM3 runs. The impacts projected by various climate models and their ensemble members are quite diverse as illustrated in Chapter 5. Four climate products have been considered: the original HadRM3, the bias-corrected and downscaled RCMs from the Future Flows (FF) project, the

Spatial Coherent Projections and the original UKCP09 change factors from the Land Projections. They all originated from the HadRM3 projections and have undergone different types and level of processing, and thus include different additional uncertainty factors. Three of these products, the FF group, the SCP and the UKCP09 product, have been used in various climate impact studies for droughts and floods in the UK. The original RCMs, meanwhile, are less used in its original form without further bias correction in the projections or subsequent impact results. These four different products point towards a general climate trend: compared to the 1961-1990 baseline, the period of April to September will become drier while the remaining months will become wetter. This change in seasonal pattern is more pronounced if the increasing trend of PET is included in the analysis. These climatic changes subsequently affect the stream flows, in particularly the River Rother-the main surface water source of the Sussex area. Analysis on the low flows of the River Rother and the correlation between the observed flows and the drought indicator SPEI shows that under dry conditions, the summer flows become strongly dependent on the winter rainfall (refer back to Figure 6.2). As such, the Sussex water resource system needs to plan for the diminishing summer supply. The risk from diminishing summer supply can be abated to a certain extent by the increase in winter flows; nevertheless the risks remain since the annual water balance is generally lower than that of the 1961-1990 baseline period.

Aside from the climate uncertainty that these products represent, there also exists post-processing uncertainty from different sources of information, even within the 1961-1990 baseline period. This bias was partially accounted for by comparing the projections of each product against the baseline of the same product. Amongst the climate products, the 10,000 realisations of the UKCP09 product demonstrate a wider range of drought frequencies than the other 11-member products. The SCP product, despite being described as the closest to the UKCP09 product, projects a smaller span of drought frequencies and depending on the drought types, is within a comparable range to the frequency ranges of the RCM and FF group. Yet, when this post-processing uncertainty trickles down the uncertainty cascade, the UKCP09 product does not necessarily represent the most challenging conditions to the Sussex water resource system. The vulnerability analysis in Chapter 7 shows that amongst the products, the Future Flows conditions exert a higher risk of supply and environmental flow deficits compared to the UKCP09 conditions. This result was cross-validated by both the Simulation Model and Optimisation Model of the area. In particular, the Sussex water system appears to be robust to variations of the droughts in the 1961-1990 periods, such as those projected by the SCP and the UKCP09 group. While the UKCP09 and the SCP products represent climate change impacts, they still revolve around the pattern of past droughts, in particularly the droughts within the 1961-1990 baseline because they only provide monthly tri-decadal changes. Both the Optimisation Model and the Simulation model demonstrate that the most severe droughts within the SCP and the UKCP09 products are the 1975-1976 and the 1988-1989 droughts. These are also the most serious droughts within the 1961-1990 observed period in the Sussex area. The worst historic event in 1921-1922 did not fall within the baseline. This robustness to past droughts was achieved due to the current drought planning practice of the water companies in England and Wales. In many cases, the drought plan and adaptation decisions have been based on the worst historic droughts. Yet, when operating under a different sequence of droughts as projected by the FF time series, the Sussex water system is much less robust. The post-processing uncertainty also dominates hydrological flows: even with various hydrological model parameterisations, the flow projections are still markedly different amongst the climate products. While these climate products do not change the ranks of performance of the adaptation strategies in simulated results, they might lead to different preferential pathways under optimisation. The climate products can greatly affect the level of adaptation needs. Under the mild changes that the SCP product project, decision makers can opt for low cost, low impact and a gradual adaptation pathway. On the other hand, responses to higher drought risks of the FF information will require compound supply and demand options that also incur high investment cost. As such, the post-processing uncertainty is a major uncertainty factor in determining the adaptation plan and pathways.

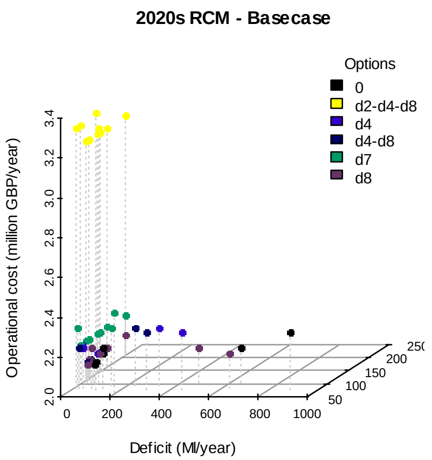
The post-processing uncertainty is also visible at the water resource model level. The Optimisation Model considers system operation under perfect information, while the Simulation Model demonstrates the actual risks under partial or uncertain information. For instance, the Optimisation Model calculates the storage of the Weirwood Reservoir and uses groundwater licenses according to the impending demand and supply. Therefore it can proactively plan the amount of water to be stored in the Reservoir, as well as reserve groundwater in views of a drought. Meanwhile the Simulation Model is rule-based and extracts the supply sources based on the demand. Due to the difference between optimisation and simulation, adaptation results under simulation are sensitive to the level of risks, in this case diminishing supply due to the changes in surface flows. Therefore adaptation planning using simulation is sensitive to climate uncertainty. Meanwhile, optimisation can better accommodate changes in water shortage risks, but as a consequent of these changes opts for different preferred adaptation plans. Consequently, adaptation planning using optimisation is sensitive to both climate uncertainty and post-processing uncertainty. Consequently, the Sussex system appears much less robust under simulation than optimisation. In practice, as climate uncertainty constitutes a major factor in adaptation decisions, the perfect information state such as projected in the Optimisation Model cannot be achieved. The system in practice is likely to be a combination of both the Optimisation Model and the Simulation Model, as the operation of the water system could be modified rather than fully rule-based.

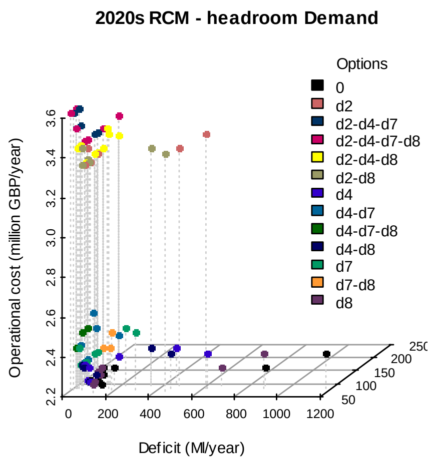
9.1.2.2.Robustness to inflow changes

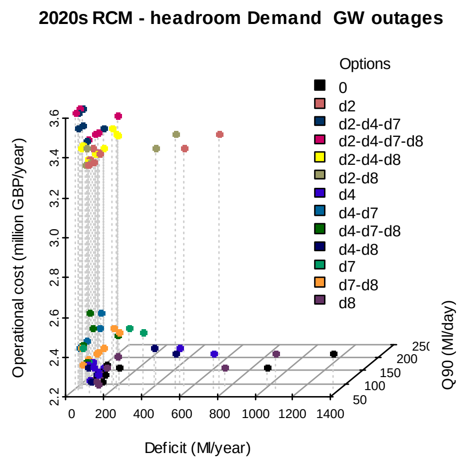
Overall, the Sussex system still shows a dependence on the River Rother flows and the supply capacity is still affected by low flows. Figure 9.1 shows the 90th percentile of daily flows (also termed Q90) (as assessed in Chapter 6) of each scenario versus its corresponding supply deficit and operational (reported in Chapter 7 and 8). It can be seen that a scenario with a low Q90 flows tends to have higher supply deficit than a scenario with higher Q90. This correlation is evident in the UKCP09 group which due to its large number of 1000 realisations could highlight the relationship between low flows and supply deficits. Chapter 8 has demonstrated that except for the Market Forces scenario, the deficits mainly occur in the Sussex North area, particularly in the transfer from Weirwood Reservoir to South East Water. This deficit in the transfer cannot be alleviated by the adaptation strategies since they are located around the Rother area and do not contribute towards the

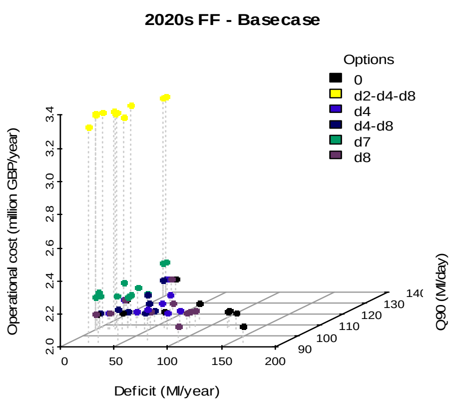
South East Water transfer. Therefore, this vulnerability can only be targeted by changing the operation of Weirwood or re-negotiate the transfer agreement with South East Water. Besides, demand management options can also be employed to reduce the water shortage risks, particularly in dry scenarios and drought periods. While the adaptation options can modify this relationship, the system remains vulnerable under the dry scenarios. In essence, scenarios with Q90 being less than 100 Ml/day are likely to experience on average an annual supply deficit of 100 Ml or more. These deficits originate from three vulnerability factors: the strong reliance of the Sussex supply system on the River Rother, bottle-necks in the system due to transfer capacity constraints, and the spatial distribution of the current options.

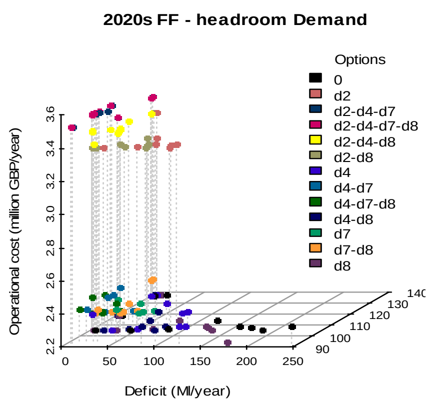
Comparison based on Figure 9.1 and 9.2 also show that the operational cost remains fairly stable for each portfolio, therefore the chosen adaptation plan might determine the future operational cost. They further highlight the comparative performance of the portfolio, for instance for the 2030s, option d2 and d2-d4-d8 are expensive options that could significantly reduce the supply deficit. However, they are of significantly higher cost compared to other potential options. In essence, for the 2030s Base case, the d4 options could achieve a similar level of supply deficit at a much lower cost.

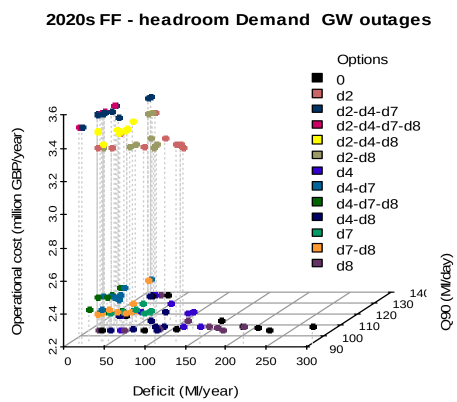

2020s RCM - Basecase
Options
0
d2-d4-d8
d4
d4-d8
d7
d8
Operational cost (million GBP/year)
Deficit (Ml/year)
Q90 (Ml/day)


2020s RCM - headroom Demand
Options
0
d2
d2-d4-d7
d2-d4-d7-d8
d2-d4-d8
d2-d8
d4
d4-d7
d4-d7-d8
d4-d8
d7
d7-d8
d8
Operational cost (million GBP/year)
Deficit (Ml/year)
Q90 (Ml/day)


2020s RCM - headroom Demand GW outages
Options
0
d2
d2-d4-d7
d2-d4-d7-d8
d2-d4-d8
d2-d8
d4
d4-d7
d4-d7-d8
d4-d8
d7
d7-d8
d8
Operational cost (million GBP/year)
Deficit (Ml/year)
Q90 (Ml/day)


2020s FF - Basecase
Options
0
d2-d4-d8
d4
d4-d8
d7
d8
Operational cost (million GBP/year)
Deficit (Ml/year)
Q90 (Ml/day)


2020s FF - headroom Demand
Options
0
d2
d2-d4-d7
d2-d4-d7-d8
d2-d4-d8
d2-d8
d4
d4-d7
d4-d7-d8
d4-d8
d7
d7-d8
d8
Operational cost (million GBP/year)
Deficit (Ml/year)
Q90 (Ml/day)


2020s FF - headroom Demand GW outages
Options
0
d2
d2-d4-d7
d2-d4-d7-d8
d2-d4-d8
d2-d8
d4
d4-d7
d4-d7-d8
d4-d8
d7
d7-d8
d8
Operational cost (million GBP/year)
Deficit (Ml/year)
Q90 (Ml/day)

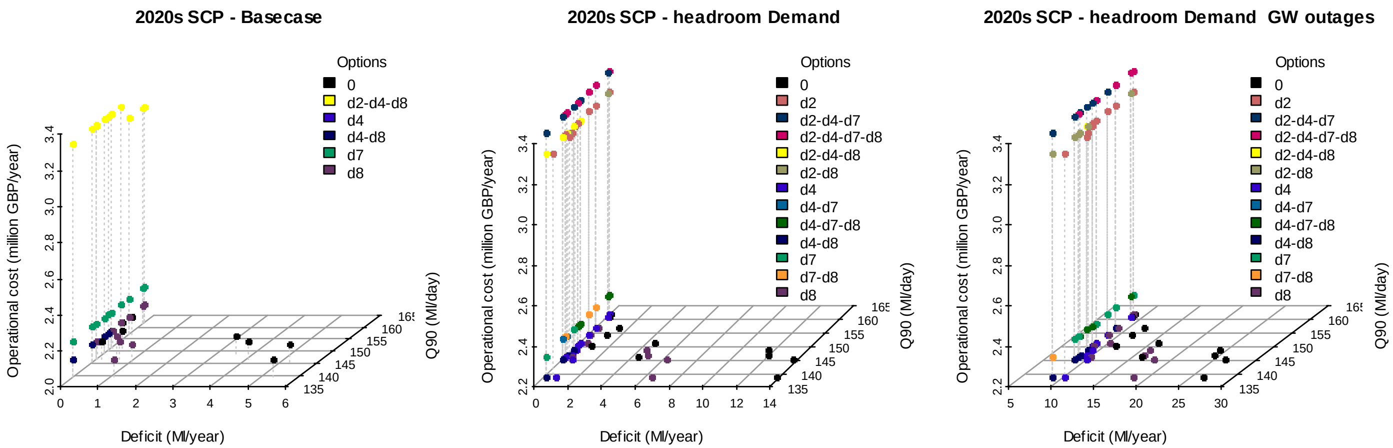
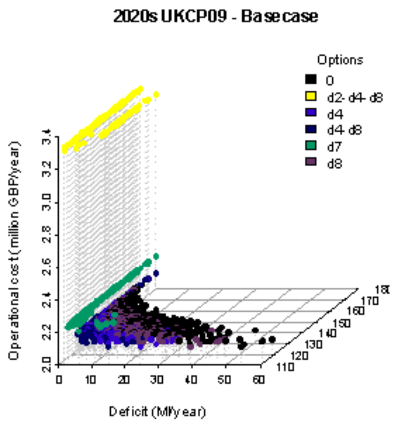
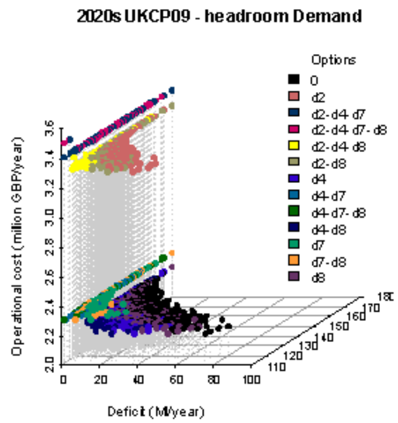
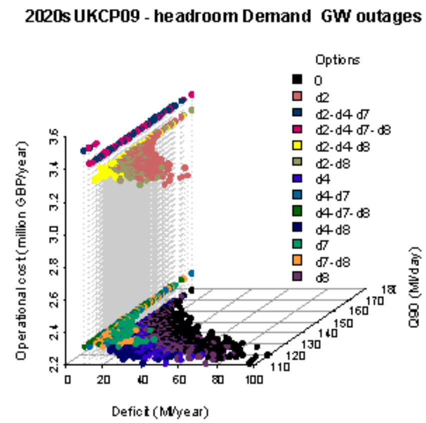
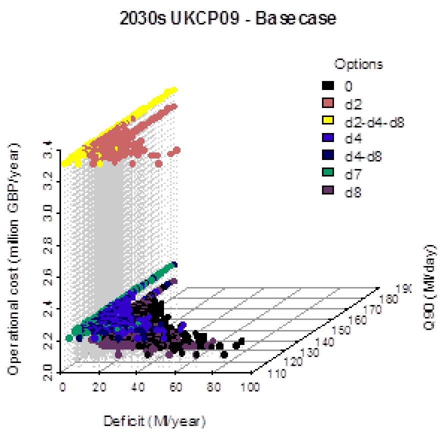


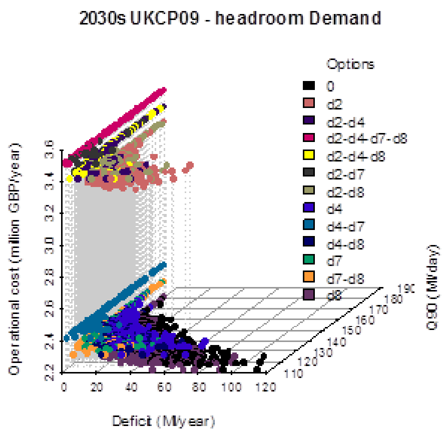
Figure 9.1 Graph of Q90-Operational Cost-Supply Deficit of the Sussex water resource system under different climate products and headroom uncertainty for the 2020s

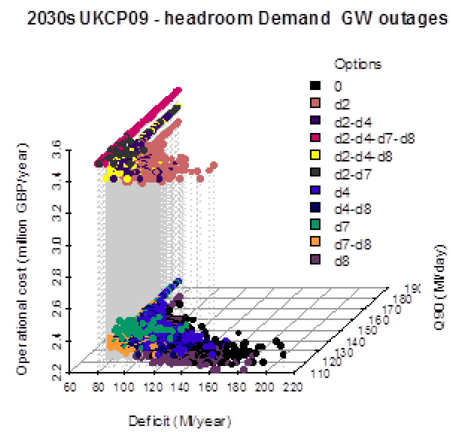

2020s UKCP09 - Basecase
Options
0
d2- d4- d8
d4
d4- d8
d7
d8
Operational cost (million GBP/year)
Deficit (Ml/year)
Q90 (Ml/day)


2020s UKCP09 - headroom Demand
Options
0
d2
d2- d4- d7
d2- d4- d7- d8
d2- d4- d8
d2- d8
d4
d4- d7
d4- d7- d8
d4- d8
d7
d7- d8
d8
Operational cost (million GBP/year)
Deficit (Ml/year)
Q90 (Ml/day)


2020s UKCP09 - headroom Demand GW outages
Options
0
d2
d2- d4- d7
d2- d4- d7- d8
d2- d4- d8
d2- d8
d4
d4- d7
d4- d7- d8
d4- d8
d7
d7- d8
d8
Operational cost (million GBP/year)
Deficit (Ml/year)
Q90 (Ml/day)


2030s UKCP09 - Basecase
Options
0
d2
d2-d4-d8
d4
d4-d8
d7
d8
Operational cost (million GBP/year)
Deficit (Ml/year)
Q90 (Ml/day)


2030s UKCP09 - headroom Demand
Options
0
d2
d2-d4
d2-d4-d7-d8
d2-d4-d8
d2-d7
d2-d8
d4
d4-d7
d4-d8
d7
d7-d8
d8
Operational cost (million GBP/year)
Deficit (Ml/year)
Q90 (Ml/day)


2030s UKCP09 - headroom Demand GW outages
Options
0
d2
d2-d4
d2-d4-d7-d8
d2-d4-d8
d2-d7
d4
d4-d8
d7
d7-d8
d8
Operational cost (million GBP/year)
Deficit (Ml/year)
Q90 (Ml/day)

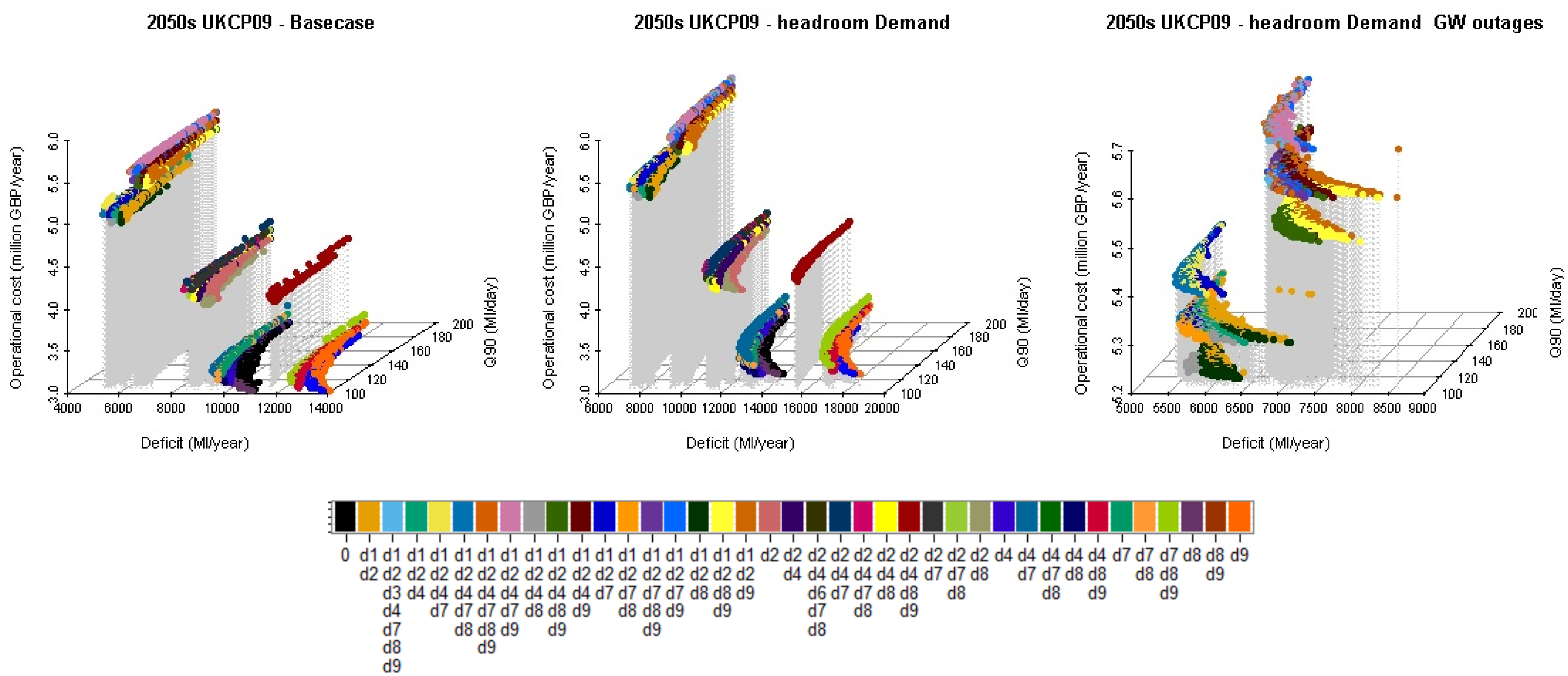


Figure 9.2 Graph of Q90-Operational Cost-Supply Deficit of the Sussex water resource system under UKCP09 for the 2020s, 2030s and 2050s Market Forces

9.1.2.3.Robustness to Demand Changes

The Sussex system could cope with climate risks and natural variability under the 2020s and the 2030s demand projections. However in the 2050s demand changes become a controlling factor on system robustness and adaptation needs. In essence, under the Innovation, Local Resilience and Sustainable Behaviour socio-economic scenarios, the adaptation plans produced by the Simulation and the Optimisation Model remain similar to those of the 2020s and the 2030s. However, to cope with the 35% growth from the 2007 demand baseline, the system will need to rely on a new desalination plant in the Brighton area and demand management measures via universal metering. The additional risks from demand growths at the headroom level and the additional groundwater outages could further test the system supply capacity. As such demand changes are an important factor in determining the adaptation needs and pace. Therefore, demand changes should be monitored and used as an indicator for potential option switch and/or retrofit. Such approach could be implemented into the 5-year planning cycle so that water management plans are designed to cope with the current risk level, but also to strategically build a robust system in view of future risks. Yet, the real socio-economic situation of the Sussex area in the 2050s is unlikely to be characterised by a single scenario; rather it will be a combination of all, with certain proportion of the population and governance gears toward sustainability while the remaining still attach to consumerism (Environment Agency, 2008). The demand growths of the four EA scenarios therefore act as a reference rather than an absolute value for potential demand growth and its uncertainty.

When different demand growth levels for the 2050s are displayed as deviations from the 2007 annual demand, it can be seen that on average the multiple option portfolios can accommodate the demand changes better than the single ones (Figure 9.3). At the same level of demand growth, the former help the Sussex system to contain the supply deficits at a lower level than the latter. At each level of demand deviation, the performance of each option also varies across the scenarios (Figure 9.4). For instance, the portfolio of Arun Abstraction, Hardham Wellfield Optimisation, and Aquifer Storage and Recovery has a more ranging performance, represented by the span of the annual supply deficit criterion, than the portfolio of Brighton Desalination Plan, 98% universal metering, Arun Abstraction and Hardham Wellfield Optimisation. Therefore the former portfolio can be considered more robust than the latter portfolio in terms of maintaining low supply-demand deficit under demand uncertainty. However, the portfolios with better and more reliable performance are often more expensive to invest and to run. Therefore the final decision rests with the decision makers on what investment budget and water shortage level that they can accept. It should be noted that these demand changes do not include specific interactions between climate change and demand growth, such as those that the CCDEW report (Downing et al., 2003) has demonstrated. To a certain extent, this growth is included in the headroom demand level; however, climate change effects on demand are likely to be seasonal and weather-dependent. Therefore it could be an additional risk in making the demand growth the controlling factor of system robustness.

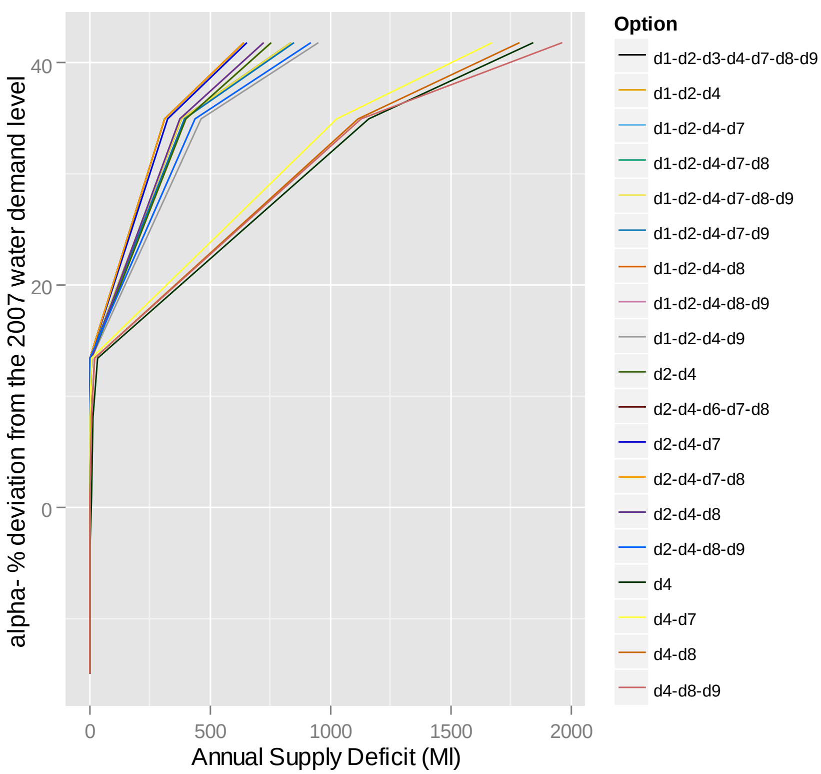


Figure 9.3 Graph of the changing overall average annual supply deficit as water demand deviates from the 2007 level

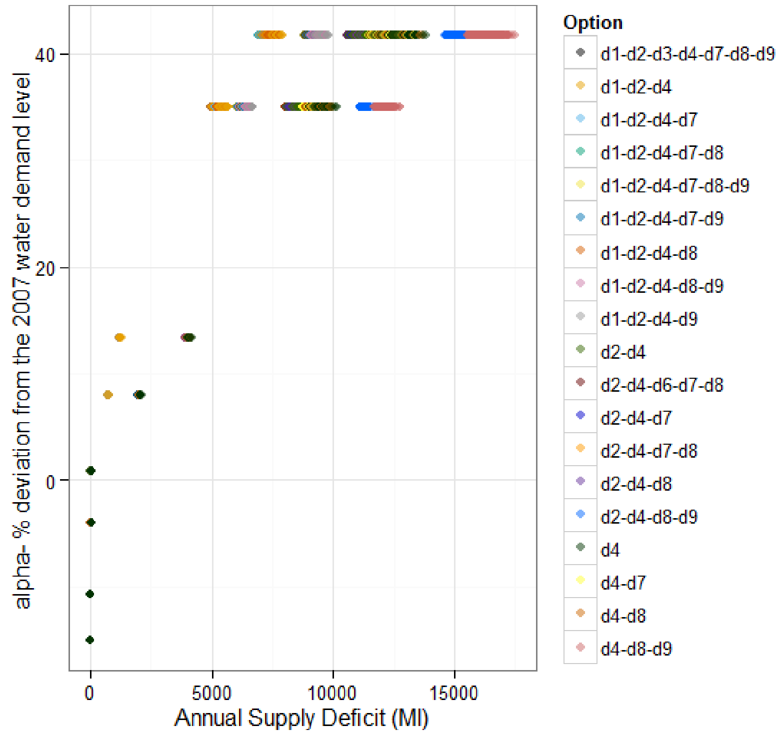


Figure 9.4 The ranging performance of each portfolio under different level of alpha

9.1.2.4.Robustness to different supply reliability

The study has considered supply reliability in surface supply under the climate change impacts and in groundwater supply in the additional scenarios of 5% reduction of groundwater supply. This reduction represents the outage risks, such as when the groundwater source becomes unavailable due to pumping faults or floodings. In its original definition outage events are temporary loss of up to 90 days; any durations longer than that are considered as out of service period. By being uniformly applied to the whole time series, to a certain extent this 5% supply reduction takes into account other potential climate change effect or supply reduction due to changes in licenses and legislation (e.g. the effect of the Habitat Directive- which is often termed sustainability reduction). In essence, this 5% reduction can include the long-term 3% loss of supply of the underlying Chalk aquifer in Sussex (Table 9.1). However, it does not implement the seasonal changes, which manifest as winter increase and summer reduction. Therefore there are still additional risks of dwindling groundwater sources in the 2050s.

Table 9-1 Potential impact of climate change on groundwater by 2025. **Source:** Environment Agency (2009)

	Sandstone[6]	Chalk[7]
Long term average recharge	9% reduction	3% reduction
Long term average winter recharge	2% reduction	2% increase
Long term average summer recharge	12% reduction	19% reduction
Middle range river flows (Q50) for rivers mainly fed by groundwater	13 to 21% reduction	6% reduction
Dry period river flows (Q95) for rivers mainly fed by groundwater	10 to 25% reduction	5 to 6% reduction

Overall, the modelling results in Chapter 7 and 8 show that groundwater outages do not pose a significant risk to the Sussex area at the 2020s and 2030s water demand level. Nevertheless it becomes a major constraint in the Market Forces 2050s since both the Sussex Worthing and Sussex Brighton are highly dependent on groundwater, the source of approximately 70% of their current water supply. Under the 2020s and the 2030s situations, these groundwater sources can accommodate the water demand, but the 2050s Market Forces level requires the need of additional supplies from desalination. Under high demand level and groundwater outages, the constraints on transfer capacity between Sussex North and Sussex Worthing as well as between Sussex Worthing and Sussex Brighton can also lead to system collapse. As most of the adaptation strategies rely on the Rother area, transferring water from this area towards other resource zones will become a key need for future adaptation plan. Moreover their total supply inputs are restricted by the treatment capacity of the Hardham Water Treatment plan, which can sufficiently be reduced during floods. Therefore, the system is at risks not only during prolonged droughts, but also during floods. Asides from the d3 option, which enhance the transfer from the Rother area to the Weirwood and Worthing area, the system might need further transfer enhancement to abate the risk of demand growth and groundwater outages. Consequently, in order to be robust to the varying reliability level of supply sources, the system needs to implement other options than the nine options being considered in this study, so that it can successfully cope with outages in the Worthing and Brighton area. In this study, the transfer between Portsmouth Water and Sussex North was assumed to be perfectly reliable. Nevertheless, water transfer amongst water companies could still be under the threats of prolonged regional droughts. In the Sussex area, the transfer from Weirwood Reservoir to South East Water has been shown to be highly susceptible to drought risks. The potential risks of transfer failures thus should be considered in adaptation plans and further analysed in a wider regional context.

9.1.2.5.Robustness to adaptation plan switching

Due to the richness of options, the Sussex supply system can be gradually enhanced in its coping capacity; therefore it can accommodate the flexibility aspect of the robustness concept. The options identified in Chapter 8 enable several adaptation pathways. These pathways are dependent on the budget and risk averseness of the decision makers, as well as the climate product that the plan is based on. In the 2020s, single-option plan such as universal metering (d2), smart operation of an existing supply source (d8-Wellfield Optimisation), Arun Abstraction (d4), Ford Effluent Reuse (d7) or a combination of d2-d4-d8 or d4-d7-d8 could enhance the robustness of the Sussex resource system.

In practice, since the publication of the 2009 Water Resource Management Plan (Southern Water, 2009b), the company has implemented option d4, thus orientates the adaptation plan towards option portfolios involving the Arun Abstraction. Therefore the company can choose to rely on d4 or additionally implement universal metering, Wellfield Optimisation or Ford Effluent Reuse. As the adaptation needs in the 2030s do not differ substantively to the 2020s, the decision makers can choose to enhance their 2020s options or extend from the single or double option into a portfolio of three options. In the 2050s, the adaptation pathways would depend on the level of demand growth. Under the Innovation and Sustainable Behaviour scenario, the Sussex system can still rely on its 2020s and 2030s composition. As the Sustainable Behaviour scenario projects a lower demand level than the 2020s and 2030s, the system can even revert back to just using Wellfield Optimisation or Arun Abstraction.

On the other hand, under the Local Resilience scenario, the system is likely in need of additional options that have not been selected in the 2030s. To accommodate this

8% demand growth, depending on the climate scenario, the Sussex system relies on universal metering to reduce demand, Arun Abstraction, Ford Effluent Reuse and additionally the Aquifer Storage Recharge in Worthing (d9). While this d9 option is not selected in all the scenarios of UKCP09 or FF, its occurrence indicates potential risks of shortages in Worthing that have activated the option. Overall the common portfolios in the Local Resilience scenario should contain two or more options. Universal metering starts to appear as a key option under this socio-economic scenario. In contrast to other socio-economic scenarios, the Market Forces scenario projects a steep increase in water demand and prompts the implementation of all available adaptation options. In particular, under this scenario, universal metering and desalination become the core strategy that occurs in every adaptation plan. Aside from these two options, the system also needs addition implementation of d4, d7 and d8. D4 and d7 tend to not overlap in the medium impact portfolio; these plans often include either d4 or d7. Under headroom demand and groundwater outage risks, the whole option set is often selected. Out of the two desalination options for Brighton (d1 and d6), the higher capacity design were selected by the Optimisation Model due to the severity of water shortages. As d1 and d6 are mutually exclusive, the d6 option was not featured in the adaptation plan for the Market Force 2050 scenarios. Overall, the potential adaptation plans across the 2020s, 2030s and 2050s period show that the Sussex system can accommodate flexibility in their planning.

As an example, Figure 9.5 and Figure 9.6 demonstrate the potential adaptation pathways under climate risks projected by the FF product under different demand profiles, namely baseline demand, headroom demand and headroom demand with groundwater outage risks. In particular, Figure 9.5 shows the most robust options, selected as the options with the smallest worst-case scenario deficit. If there is more than one option that can achieve that level, the selected option is the option with the lowest investment cost. On the other hand, Figure 9.6 shows other available options that could keep the maximum water deficit under 150 Ml/year. A comparison between the two figures show that the most robust option is not always needed to obtain this level of performance. Under baseline demand, while the combo of d2-d4-d8 is the best available option for the 2020s, it is not strictly needed for the deficit target of under 150 Ml/year. Figure 9.6 demonstrates that this target could be reached using either d8, d4, d4-d8 or d7. Similarly, d2-d4-d8 is still the best available option with least cost, but the set of d4-d8 is sufficient for the target. Yet, moving to the 2050s, under Market Forces and Local Resilience, even the most robust set of options could not keep water deficit under 150 Ml/year. The decision makers therefore need to consider other options or be prepared to cope with deficit risks of more than 150 Ml/year.

Figure 9.5 and 9.6 also demonstrates the need of additional options under increased risks. Under baseline demand, the best available least cost option for the 2020s and 2030s is the d2-d4-d8 set; however, under the headroom demand, this set starts to show limitations in supply capacity, and as a result, performs less well than the d2-d4-d8-d7 set. Moving to the 2050, d1 appears to be an essential additional to the most robust set under the Innovation socio-economic scenario. A similar phenomenon was observed in Figure 9.6. Under the baseline demand, the single option d8 is the least cost acceptable option. However, under headroom demand, d8 is not sufficient and the least cost acceptable option is now the d2 option. Meanwhile, under the Innovation scenario in the 2050s, d7 is an acceptable option for baseline demand, but not so under headroom demand. Under headroom demand, it needs to be coupled with either d4, d8 or d2 to achieve the target deficit threshold.

As such, demand uncertainty dominates the 2050s, as the specific demand profile and socio-economic scenarios could determine adaptation outcomes. In the Market Forces and Local Resilience scenario, there is a limit to adaptation since even the most robust set of options cannot restrict water deficits to under 150 Ml/year. As such, additional iterations which reconsider other potential options and the interval of acceptable performances (refer to Figure 3.4) might be beneficial. In particular, these additional options should address the vulnerabilities identified in Chapter 7, such as the transfer bottle-neck between Hardham and the Weirwood area, and enhance the Weirwood part of the supply network. On the other hand, changing the acceptable risk level could also be a useful exercise to explore other potential coping schemes, which should also tackle the cascading effects of such risk level.

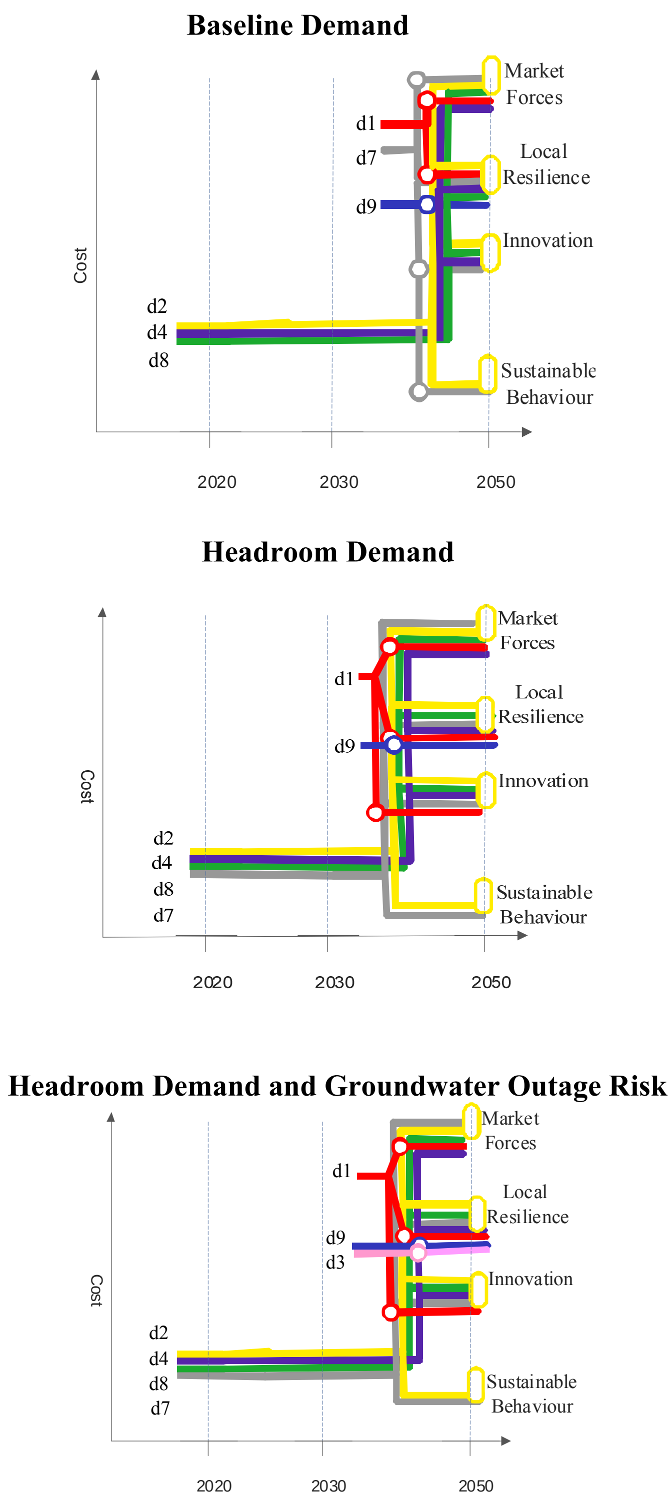


Figure 9.5 The most robust adaptation pathways to cope with drought risks projected by FF**.** The interchange sign indicates when an option joins the portfolio.

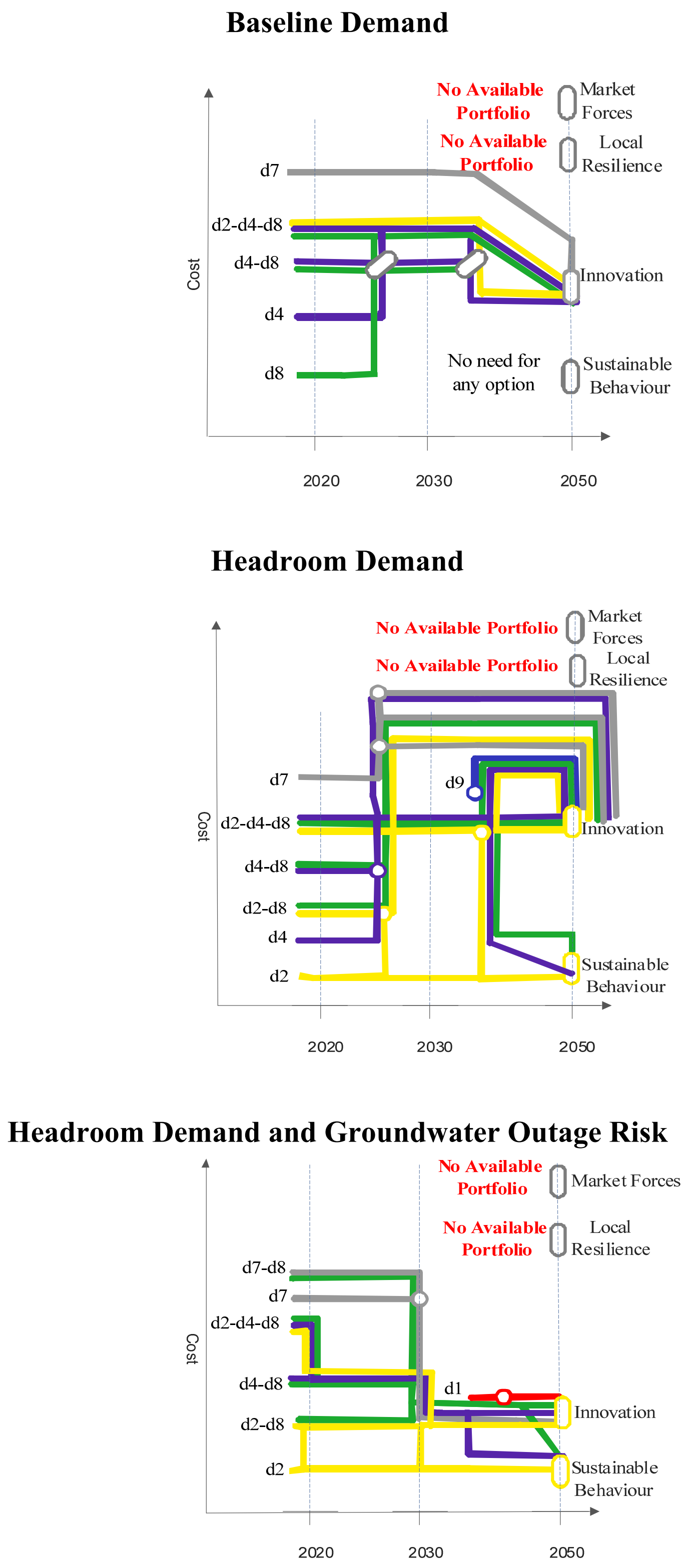


Figure 9.6 Available adaptation pathways to maintain water supply-demand deficit to under 150 Ml/year in all scenarios. The interchange sign indicates when an option joins the portfolio.

9.2.FACTORS TO ADAPTATION SUCCESS- A WIDER CONTEXT

The last section has presented robust decision analysis for the Sussex area in a modelling context. This section subsequently aims to discuss the adaptation decisions in a wider context, including the underlying assumptions in the modelling process. Via an integrated assessment of the uncertainty cascade, the study has demonstrated that the Sussex water resource system can become robust via a flexible and sequential implementation of options. However it still remains susceptible to potential risks from post-processing uncertainty, demand uncertainty and source reliability uncertainty. A key feature of the current Sussex system as well as of the future plans is the high dependency on the Rother area. Nevertheless all the supply options in the Hardham area has to route via the Hardham Water Treatment plan, which is still restricted by the 75 Ml/d treatment capacity. This vulnerability factor has not yet been addressed in the current adaptation plan. Moreover the spatial concentration of the options around this area can place additional strains on the links and network in the Rother area. Under such strains, the link failure and leakages can be a key impediment to adaptation success. Finally, while being presented as distinct options in the plan, these options are still likely to connect hydrologically. In a wider context, the area shares the Chalk aquifer with other water companies, who are also extracting water from the rivers and the aquifer. The River Rother is quite well connected to the underlying aquifer, and therefore its base flow can potentially be affected by activities in its proximity or within the same aquifer. As such, the adaptation plan should also consider other options that are located elsewhere and can diversify the supply to the system.

Aside from the supply augmentation option, the system can also rely on demand management to reduce the dependency on the supply side. In this study demand management has been considered in the form of universal metering that is assumed to reduce the demand level by 10%. However, the prospect of that reduction level is far from clear. Until 2003, the metering statistic was only 28% and most of the demand data was based on supply and leakage estimation. As both demand data and leakages were estimated, they are highly unreliable. As the current metering proportion stands at 50-70%, the new demand data have been rapidly accumulated.

However the lack of long demand records still impedes research on the demand pattern associating with different household demography, weather signals and demand management measures. Deep uncertainty still plagues demand projections. An OFWAT report in 2007 cited a UK Water Industry Research (UKWIR) study stating that socio-economic and climate factors determine 60% of the variation in pcc and the remaining 40% could not be explained. It was speculated to be due to other factors, including the different pcc accounting methodologies used by companies and data error of the demographic variable.

The current level of per capita water consumption in the Sussex area is approximately 150 l/p/d on average and via metering is hoped to reduce to the 136 l/p/d level. The basis of the universal metering option has relied on the assumption of reducing consumption if the users are metered and charged. Additionally metering data will help water companies to identify the leakage locations and further eliminate this loss. In comparison to the 2050s socio-economic scenarios, the Innovation scenario assumes a pcc of 125 l/p/d, the Market Forces 165 l/p/d, Local Resilience 140 l/p/d and the Sustainable Behaviour 110 l/p/d. If these assumptions hold, universal metering could help shape the 2050s toward the Innovation or the Local Resilience scenario. However a robust adaptation plan should not assume and rely on automatic demand reduction via metering. There is uncertainty surrounding whether that phenomenon of demand reduction is wide spread or can sustain over time. In reviewing past changes, Sharp (2006) has shown literature supporting this assumption (Baker and Toft, 2003; Jeffrey and Gearey, 2006) but also warned that the effect varies with different groups of water users and can result in different response pattern; domestic customers are also less likely to change their consumption amount than commercial customers (Achttienribbe (1998) in Sharp, 2007).

An EA report on household water metering has also found price elasticity, the changes in consumption due to 1% changes in price, of -0.14% in South East England. The assessment by Herrington (2005) estimated a higher reduction of -0.20 to -0.25 over the summer. Based on these figures, the 10% demand reduction in the d2 option will require a 4%-9% increase in price. While this change is comparable to the past price trend, its effects should be considered in a wider context of how the consumers of different cohort will respond. According to the Consumer Council for Water (2010), in 2009 a household in the South East spent on average £5.94 per week and for 11.9% households, that constituted more than 3% of their expense. Another survey by the Family Resource Survey, a survey on 25000 samples in the UK, estimates that the average spending on water accounted for 1.8% with and 2% without water meters of net household income. Therefore the changes in water price and tariff should be considered with regard to its socio-economic effects. As pcc is determined by consumption behaviour, changes in consumption at the micro level should also be considered and accommodated. The Family Resource Survey also shows that the household size and composition can also affect the water bills and water pcc. With similar demographic structure, a larger household tends to have higher water bills than a smaller household; however the average pcc of the larger household is often less than that of the smaller one. As future household size, demographic structure and household numbers will also affect the pcc and the overall metered water demand, there is a need to further incorporate demand uncertainty into future assessments.

Finally a robust adaptation decision should go beyond least-cost planning and is not restricted by the analysis boundary. As demonstrated in Chapter 8 and Section 9.1, both Arun Abstraction and Ford Effluent Reuse are two strong candidates for the adaptation plan. The Arun Abstraction option was more often selected due to their smaller investment and operational cost. Yet, in a wider context, the Ford Effluent Reuse can offer additional benefit since it treats and recycles the effluents. It does not extract additional water from the supply and instead increase efficiency of water usage. It also reduces the need of large-scale infrastructures. As many water companies now manage both water supply and effluences, the overall benefit can outweigh the financial cost. Such added benefits however were not considered in this study due to its focus on water supply. The adaptation pathways in this study are likely to represent interests to cope with water supply shortages due to drought risks. This scope while helps focus the study, may potentially affect the adaptation capacity to other elements such as floods, water quality and the ecosystems. Therefore robust adaptation decision making should take a holistic approach that integrate aspects of risks and vulnerability to the system, in order to find an adaptation pathway that considers and accommodates all the key risks.

Chapter 10. CONCLUSIONS AND RECOMMENDATIONS FOR RESEARCH

At the onset of the study, the research has specified two research questions regarding the roles of climate uncertainty in drought planning decisions and whether the different aspects of robust decision analysis can be implemented in such assessment. This chapter outlines the key findings, implications and recommendations arising from the research with reference to the research aims and objectives in Chapter 1. It summarises the results of the integrated uncertainty assessment in this study, implications for robust adaptation decision making within the scope of the study and beyond, as well as discussing the limitation of the research and recommendations for future research.

10.1.REVIEW OF RESEARCH AIMS AND SUPPORTING FINDINGS

As specified in Chapter 1, the study aims to explore the components in the uncertainty cascade from climate projections, hydrological modelling, water resource modelling and option identification. The scope is strategy assessment of a drought planning case study in Sussex, southeast England. The focus is uncertainty in climate change impacts on surface water quantity and how it interacts with hydrological modelling and socio-economic uncertainty. The research follows three specific objectives that will be reviewed and assessed in Section 10.1.1 to 10.1.3.

10.1.1. Review different definitions and approaches of the concept of robustness in water resource planning:

Chapter 2 has discussed the option robustness and the system robustness definition and the approaches each group contains. In terms of characterising robustness, there are the statistical approach, which focuses on options with the highest possibility of being the optimal given the uncertainty; the crisp set-based approach, which considers the number of available options before and after the decision; and the fuzzy set approach, which compares the system failure risks before and after a decision. Robustness approaches in water resource planning include methodologies as follow

- **Robust optimisation** often treats adaptation as capacity expansion under uncertainty, so that the system has sufficient supply capacity for projected demand given the projected climate change impacts on water resources.
- **Real Option Analysis** focuses on the sequential decision making given the future options and uncertainty. The methodology emphasizes the opportunity cost of option implementation at different decision points. For instance, it examines the comparative Net Present Value of implementing option A at year 1 versus year 5, and whether that decision will exclude other adaptation pathways.
- **Info-gap Decision Theory** explores the deterioration of strategy performance if the climate conditions and water demand deviate from the base case design. A robust info-gap strategy would be able to maintain its performance to the largest bound of deviation compared to other options.
- **Robust Decision Making** focuses on characterizing vulnerabilities of the system under a large ensembles of scenarios and interacts with the decision makers to identify and assess options for vulnerability reduction

These four approaches have been applied to planning problems in water resource management. Yet, they are often applied separately. Chapter 2 has subsequently proposed a framework that allows switching amongst the methodology depending on the decision objectives and level of uncertainty. Chapter 7, 8 and 9 then further engaged aspects of these approaches, by employing robust optimization and robust decision making to identify packages of options and vulnerabilities of the Sussex water resource system.

10.1.2. Conduct a case study in south-east England that incorporates the main aspects of the robustness concept:

Chapter 4 to 9 have presented a case study of robust adaptation in planning practice. The study area is the Sussex area and the scope is robust adaptation for the 2020s, 2030s and 2050s. Each of these periods was considered as a 30-year period, namely 2010-1039, 2020-2049, and 2040-2059. Aside from climate uncertainty, the study has integrated uncertainty from hydrological modelling, socio-economic scenarios and water resource modelling. The climate uncertainty was represented by scenarios and projections from different products of the Regional Climate Model HadRM3, namely the original ensembles, the downscaled and bias-corrected ensemble from the Future Flows project, the Spatial Coherent Projections and 1000 Latin Hypercube samples of the UK Climate Projections UKCP09 10000 realisation. The socio-economic scenarios for the 2050s were produced by the Environment Agency in England and Wales and contained four scenarios, namely the Innovation, Market Forces, Local Resilience and Sustainable Behaviour scenarios.

Overall the Sussex water supply system is susceptible to water shortage. The risks are mild in the 2020s and 2030s, but can be significantly high under the Market Forces scenario in the 2050s. The vulnerability mainly comes from the delivery network attributes such as the location of major supply sources and transfer constraints and the lack of alternative supply in certain demand nodes. Chapter 9 has further shown that the vulnerability is strongly dependent on demand scenarios and flow conditions. In particular, without adaptation, a 35% demand increase from the 2007 baseline will pose extreme challenges to the system and threaten a complete supply collapse. Meanwhile Q90 low flows in the River Rother, Sussex's major supply source, of approximately 100 Ml/d could start to trigger water shortages in the scenario or ensemble. Yet, the adaptation process in Sussex water management could accommodate both aspects of the robustness concept, as well as complementary implement different robust decision approaches.

In this study, the Robust Optimisation method was employed to identify the optimal option set in 133 scenarios in each time slice (100 UKCP09 scenarios, 11 RCM ensemble members, 11 FF ensemble members and 11 SCP scenarios). A Sussex simulation model is then used to test these options under all scenarios, in essence testing the performance of optimal options in single scenarios on the full set. Therefore, the analysis could analyse potential 'satisficing' factor when an option is not optimal in all scenarios but performs acceptably well in the sub-optimal cases to become the robust strategy. The optimisation process was done with the objectives being minimising environmental flow deficit, minimizing water supply deficit and minimising the system operation and investment cost.

The study did not indicate a specific robust measure as the recommended adaptation plan for Sussex; instead, it presents the options along with their performance and costs for the decision makers to select. In general, the compound options are often more effective than single options in abating supply deficit; however, they also entail a higher cost, which requires careful sequential planning based on system vulnerability in the 2020s, 2030s and 2050s. Robust decision analysis in the study indicates that the Sussex supply system can sufficiently provide water for the Sussex North, Sussex Worthing and Sussex Brighton area in the 2020s and 2030s. The risk of water shortage is low and can be remediated by single options of Arun Abstraction, Ford Effluent Reuse, universal metering and Wellfield Optimisation. In the 2050s, the Innovation and Sustainable Behaviour socio-economic scenarios still maintain the low risks and the Sussex system can retain the composition of the 2020s and 2030s. Nevertheless, under the 8% and 35% demand growth of the Local Resilience and Market Forces, the system will be likely under risks and need additional strategy. Depending on the acceptable shortage risks, the system might need to include any optimal option that it has not implemented in the 2020s and 2030s. Flexibility, or planning robustness, could be achieved since adaptation strategies could be incrementally built over the time periods, by moving from single option to option portfolios. Yet, the study has also shown that the current options are not sufficiently robust under the Local Resilience and Market Forces socio-economic scenarios. Therefore, new options aside from the current options and new potential acceptable risk levels should be further explored.

10.1.3. Use robust decision making to demonstrate how the uncertainty components could affect the performance of adaptation options:

Amongst the uncertainty factors investigated, demand uncertainty, climate uncertainty and post-processing uncertainty appear to be the controlling factor. The 2020s and 2030s is dominated by climate uncertainty and climate post-processing uncertainty. In essence, climate uncertainty in each climate product leads to the varying performance of adaptation options. This uncertainty dominates hydrological uncertainty of the hydrological model CATCHMOD. However, post-processing uncertainty is also a major uncertainty element and overall could change the preferential adaptation pathways. Under the SCP product, there is little need for the system to adapt to climate change impacts. Meanwhile, the FF and UKCP09 both require incremental adaptation plans in the 2020s, 2030s and 2050s. Since the RCM projects much drier conditions, it leads to more extreme plans and require more strategies than other climate products; however, RCM is often not used without bias-correction in impact studies and therefore was included only for reference in this study. The RCM product, however, could indicate the preferential order of adaptation options, and therefore can be used instead of other climate products if the objective is option comparison. Moving to the 2050s, demand uncertainty becomes the major controlling factor of adaptation options. While information and climate uncertainty are still exhibited in the scenarios, the level of demand is the key influence of the overall adaptation plan. Moreover, it can also affect the adaptation pathways from the 2020s to the 2050s. In particular, under the Innovation and Sustainable Behaviour scenarios, the adaptation pathways will mainly be single or double options and the decision makers can rely on short-term planning or reactive adaptation. Meanwhile, under the significant risk and requirements to adapt in the Local Resilience and Market Forces, adaptation pathways will need to be planned well in advance, adaptively adjusted. Under these cases, decision makers will need to focus on system vulnerability and system renovation. Monitoring key indicators of climate change impacts and demand growth, such as the Q90 flows and the level of annual water demand, could also help identify potential intervention points of option switching.

10.1.4. Key findings

The key findings of this study include

- A new methodology of robust decision analysis that combines Robust Optimisation and Robust Decision Making to include dynamic risk preferences and the comparative option performances under certainty and uncertainty
- A case study that integrates a cascade analysis of the climate uncertainty, climate post-processing uncertainty, hydrological uncertainty, water resource model uncertainty and demand uncertainty on water resource planning
- The recognition that climate post-processing uncertainty, in addition to other uncertainty mentioned in the literature, can also affect the adaptation plan:

This uncertainty has been shown to dominate other types of uncertainty for this particular case study

- An analysis that shows that vulnerability is dependent on the local conditions and the planning option: in the Sussex case study, despite the climate post-processing uncertainty of different climate products, main vulnerability of the system remains similar. The vulnerability is due to the high dependence of the system on the water sources around the Hardham area and the limited access of these sources from other areas. Since the options are also mostly located around this area, the Sussex water resource system remains vulnerable in terms of maintaining the transfer agreement between Southern Water and South East Water
- A demonstration of different decision sensitive conditions that prompt option selection under different level of water shortage: These sensitive conditions can potentially help the decision makers to construct their adaptation plans and pathways

10.1.5. Limitations

The study has to a great extent achieved its aims and objectives. Yet there are several limitations remaining. Firstly, the study has not integrated hydrological uncertainty into the final adaptation decision analysis. While climate uncertainty dominates hydrological uncertainty overall, there is still a need to further integrate hydrological uncertainty in future research. Secondly, the study could also further be improved by reducing the difference in network configuration in the optimization and the simulation model. In essence if the simulation model can accommodate a higher resolution of the Sussex network, further comparative results on vulnerability, particularly the vulnerability hotspot in the network, could be conducted. Thirdly, the study has not explicitly included climate change uncertainty in groundwater supply and demand patterns. Finally, the options considered in this study mainly are mainly constituted of supply option. The study therefore would benefit from an expansion of available options, in particular demand options that engage water efficiency and rainwater harvesting.

10.2.IMPLICATIONS FOR ADAPTATION POLICY AND PRACTICE

The study has several implications for adaptation policy and practice. Firstly, it demonstrates that various aspects of the robustness paradigm could be implemented in practice. The options considered in this study are management options considered by Southern Water in their option appraisal. The study has therefore identified robust and transformable options and pathways for the Sussex system that along with the current planning practice, can contribute toward low vulnerability and robust adaptation of the Sussex water resource system. Furthermore, it has demonstrated key vulnerabilities and vulnerability threshold of the area that can help decision makers to monitor potential need to adapt and address the issues. Overall the study has indicated Arun Abstraction, Ford Effluent Reuse and universal metering as core options for the adaptation plans and pathways to accumulate from. It has also demonstrated that vulnerability is largely determined at the local level, in this case due to the network attribute of the supply system.

In terms of practice, the study has indicated the needs to further implement demand management and revisit assumptions regarding these measures. In terms of methodology, the study has proposed an integrated modelling framework of robust decision making for a large set of options. In practice, water companies often have to consider various strategies in parallel and the original Robust Decision Making requires a significant of model runs under such circumstance. For instance, the nine management options of this study would have constitute 2^9 sets of options without a pre-selection process; once coupled with the 1000 climate scenarios, 4 demand profiles and 3 headroom uncertainty (the base case demand, the headroom demand of 5% increase and the headroom demand associating with 5% groundwater reduction), the high number of scenarios is exceedingly time and computationally expensive. By using robust optimization to reduce the set to 39 feasible cases, the approach shortened the simulation and analysis time to an acceptable scale to water companies. This approach in essence will reduce the model runtime to nearly a day, and thus, can be employed in real water planning practice. Furthermore, the study has shown a combination of analysis originating from real option, info-gap and robust decision making. It therefore demonstrates their complementary application despite their seemingly parallel ideologies.

Yet, the challenge of decision making under deep uncertainty remains. While the study could integrate the different uncertainty components in a research study, a similar analysis in practice is significantly time demanding, particularly when the number of planning options explodes. Such analysis faces the challenges of converting different climate data formats and resolutions into data that is relevant to a water resource scale, constructing or adjusting the relevant hydrological and water resource model, analysing the amount of data and interpreting the different dimensions of uncertainty interactions. Therefore, in order to encourage robust adaptation in practice, changes should be made to make data from the different climate products readily available in an accessible and consistent format. There is also a need for decision support tools that could integrate the uncertainty and present the outcomes in informative visualisation and presentation.

Finally, the study has presented decision making in a holistic context, where climate uncertainty is only one of the controlling factors of adaptation. Yet, it has shown that with the current available climate products, adaptation pathways and decisions can be strongly influenced by the uncertainty due to different levels of post-processing from the same climate model results. This implies that water managers still face high uncertainty in practice regarding which climate products to use. As demonstrated, the UKCP09 group, while includes the highest factors of uncertainty, appears moderately inadequate to test the system. In essence, the change factor method that both the UKCP09 and SCP product use to project changes make the testing time scenarios become variations of the 1961-1990 historic time series. Since hitherto water companies still use that historic period and beyond (some even to the late 1880s), the UKCP09 and SCP essentially test water planning against the same sequence and patterns of droughts. Meanwhile, the time series-based FF and RCM project a wide variation of drought events and therefore present more adaptation challenges to the system. As such, even the choice of climate product could potentially influence the overall robustness of the system.

10.3.RECOMMENDATION FOR FURTHER RESEARCH

As discussed before, the study still includes several limitations that can be addressed in future research. There is a further need for holistic robust analysis approach that incorporates climate change impacts on water demand and groundwater. That holism should not be restricted to the modelling paradigm, but also to a bigger picture. Various uncertainty factors such as changing behaviour and water consumption pattern due to changes in water availability and cultural/social value are not quantifiable and need to be considered in parallel to the modelling process. Therefore, the study could be coupled with a qualitative assessment of vulnerability from the perspective of relevant stakeholders for a combined modelling-social science assessment. Such assessment will also be able to engage a wide group of perspectives and opinions and expand the adaptation objectives beyond flows and operational cost. Examples of additional objectives could be ecosystem services, integrated management, risk distribution amongst the stakeholders and catchment restoration.

Another direction of further research is the further integration of the simulation and optimization process to reduce structure uncertainty. The model could be constructed with internal simulation and optimization mode for a consistent network and constraint configuration. Regarding the integrated approach of different robust decision methods, the model can further extend the number of scenarios, such as a bigger sample of UKCP09, to enable real option analysis along with info-gap and RDM. Demand uncertainty and climate uncertainty could also be stochastically generated in the simulation for a bigger set of scenarios.

Finally, future projects can investigate the nexus of resilience, robustness and vulnerability under uncertainty. They can expand the scope to the factors constituting adaptation success, as discussed in Chapter 1, and further identify how uncertainty could affect these attributes and their roles.

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Appendix A-Model Descriptions

A.1. THE OPTIMISATION MODEL

The model consists of two parts: a core model which illustrates physical relations between variables and a preferential model which assists decision makers in interactively defining their aspiration and reservation level.

A.1.1. CORE MODEL SPECIFICATION

A core model usually contains given parameters, state variables, decision variables and constraints. As the focus of this study is on a water supply network, the core model takes the form of a flow network that delivers water from sources to sinks.

A.1.1.1. Network representation

The network is presented as a network of nodes and arcs. A node can receive external input I*(n,t)* from a stream or a groundwater borehole, and/or outputs O*(n,t)* to satisfy water demand of a residential area. In each weekly time step *t*, water supplied to node *n* is denoted *s(n,t)* and water consumed is *d(n,t)*. If the node represents a reservoir, it will also have a storage capacity *ResCap(n)* and real time storage state *ResState(n,t)* that may change with time.

Nodes are connected by arc which has a transfer capacity LC(n,m). Flow from node *n* to node *m* may vary with time and is denoted *f(n,m,t);* likewise, *f(m,n,t)* represents flow from node *m* to node *n* at time *t.*

A.1.1.2. Strategy representation

A binary decision variable X_i (t) will represent the strategy considered. The variable will take the value of 1 if implemented and 0 otherwise. For instance, if decision X_1 is not built during time step 0-2, $X_1(0{:}2)=0$; if it is built and operated at subsequent time steps, it will take the value of 1 then on.

- The variables can adjust external input into node *n* such that

$$I(n,t) = I_0(n,t) + \Delta I_i(n) * X_i(t) \qquad \textbf{Eq.[1]}$$

In which $I_0(n)$ is the original external input into node n if no decision is implemented

$I_i(n)$ being the effect of implementing strategy X_i on available input at node *n*

- Alternatively, the variable can change the required external output (in effect mimics demand reduction due to strategy implementation)

$$O(n,t) = O_0(n,t) * [1 + \Delta O_i(n) * X_i(t)] \qquad \textbf{Eq.[2]}$$

In which $O_0(n)$ is the original required output from node n if no decision is implemented

$O_i(n)$ being the effect of implementing strategy X_i on required output at node *n*

- Finally, the variable can augment transfer capacity of an arc

$$LC(n,m,t) = LC_0(n,m) + \Delta LC_i(n,m) * X_i(t) \qquad \textbf{Eq.[3]}$$

If the strategy is not implemented, decision variables that can provide additional supply are modelled as a fictional source which is not connected to other sources (Figure 1). This setup also allows calculating the real usage of the option (e.g. the supply provided by the decision variable and the frequency of source usage).

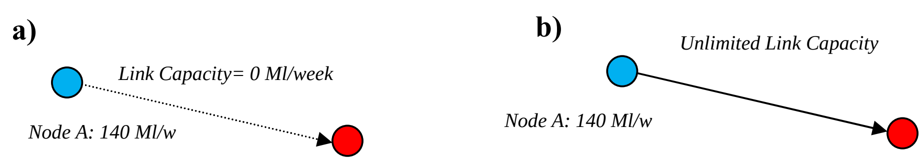

Figure 1. Schematic of how supply decision variable is implemented: a) When the strategy is not implemented, the node is not connected to the network; b) once it is connected, the link connecting the node and the network is active

A.1.1.3. Model equations and constraints

The model is governed by water balance equations. Nodes are connected by flows along the arcs. At each time step, the node can have an internal supply, internal demand as well as additional inflows and outflows from its connecting arcs. As such,

Total inflows into node *n* is denoted

$$Inflows(n,t) = \sum_{m}^{M} f(m,n,t) \quad \textbf{Eq.[4]}$$

Total outflows from node *n* is

$$Outflows(n,t) = \sum_{k}^{K} f(n,k,t) \quad \textbf{Eq.[5]}$$

- At each non-reservoir node, the following flows conservation equation applies

$$Inflows(n,t) + s(n,t) = Outflow(n,t) + d(n,t) \quad \textbf{Eq.[6]}$$

Deficit, if any, is calculated as

$$Deficit(n,t) = O(n,t) - d(n,t) \quad \textbf{Eq.[7]}$$

A node cannot supply more than what is available, nor should it get more water than its need. Moreover, flows are restricted by available transfer capacities of the arcs. Subsequently, supply, demand and flows at node n is subject to constraints as follows

$$s(n,t) \leq I(n,t) \quad \textbf{Eq.[8]}$$

$$d(n,t) \leq O(n,t) \quad \textbf{Eq.[9]}$$

$$x(n,m,t) \leq LC(n,m,t) \quad \textbf{Eq.[10]}$$

- At a reservoir node, the node has additional storage capacity and the ResState variable reflects that changing in storage as follows.

$$ResState(n,0) = ResState_0(n) \quad \textbf{Eq.[11]}$$

$$ResState(n,t) = ResState(n,t-1) + Inflows(n,t) + s(n,t) - Outflows(n,t) \qquad \textbf{Eq.[12]}$$

The node is subject to constraints as follow

$$ResState(n,t) \geq ResCap(n) * \frac{minLevel(n,t)}{100} \qquad \textbf{Eq.[13]}$$

In which minLevel(n,t) is the minimum reservoir fill (%) as required by the reservoir control curve

The reservoir cannot store more than its capacity (which is the reservoir total capacity minus its dead volume)

$$ResState(n,t) \leq ResCap(n) \qquad \textbf{Eq.[14]}$$

A.1.1.4. Constraints on decision variables

Once implemented, the permanent decision cannot be reverted

$$X_i(t) \geq X_i(t-1) \qquad \textbf{Eq.[15]}$$

A.1.2. PREFERENTIAL MODEL AND MULTICRITERIA ANALYSIS UNDER UNCERTAINTY

A.1.2.1. Technical background

The core model is capable of generating one or many feasible solutions, which satisfy all specified constraints. Often, decision makers need to select one solution out of the feasible solution set X. This selection is based on the user's criteria set R^n with n being the number of criteria. Hence, each feasible solution will have an associating vector q(x) that contains the corresponding values of each criterion. A solution is weakly Pareto-optimal if no other feasible solution has better values of all criteria. Mathematically, for our minimization problem (deficit in environmental flows, operating cost and supply-demand deficit), a solution $\hat{x}$ is weakly Pareto-optimal if

$$\forall x \neq \hat{x}\colon\ \exists k\ \in [1,n]\ s.t.\, q_i(\hat{x}) < q_i(x) \qquad \textbf{Eq.[16]}$$

Consequently, a Pareto-optimal solution, or an efficient solution, is defined as

$$q_i(\hat{x}) \leq q_i(x)\ \forall\ i = 1..n$$

$$\exists i \in [1,n]\ \ s.t.\ q_i(\hat{x}) < q_i(x)$$

Eq.[17]

The aspiration-reservation based decision support method is mainly based on the set of Pareto optimal points P (or the Pareto frontier). In essence, the method defines *a utopia point* q^U that contains the best values of each criterion (e.g. $q_i^U = \max[q_i(x|x \in P)]$) and *a nadir point* q^N that contains the worst values of each criterion (e.g. $q_i^N = \min[q_i(x|x \in P)]$). The users can also specify their preference by identifying an *aspiration point* $\overline{q}$, the desired value set of criteria, and a *reservation point* $\underline{q}$, the lower bound of acceptable criterion values. [For a problem of three minimized criteria, the Pareto front becomes a surface. Include illustrative figure here]. In this way, the decision makers can specify a range of criteria values that they are satisfied with. Aspiration-led decision support strives to find a Pareto-optimal point that is at the specified aspiration level, if attainable, and closest to the aspiration level if otherwise. In addition, the user can interactively change their aspiration level to further explore the Pareto-optimal solution under that specific setting. With each change in aspiration level, the model obtains a new Pareto-optimal solution by minimizing an *achievement scalarising function* $s(q, \overline{q}, w)$.

$$s(q, \overline{q}, w) = \max[w(q - \overline{q})]\ + \epsilon \sum_{i=1}^{n} w_i(q_i - \overline{q_i}) \qquad \textbf{Eq.[18]}$$

With $q(x) \in R^n$ being a criteria vector

$\overline{q} \in R^n$ being an aspiration point

$w_i > 0$ being scaling coeffiecients

ϵ being a given small positive number, set to 10^{-4}

The methodology employed in this study utilizes a modified version of this achievement scalarising function, as used in Makowski (1994). In essence, strictly monotone functions *u_i(.)*, termed *component achievement functions*, are introduced into the achievement scalarising function as follows

$$S\left(q,\overline{q},\underline{q}\right) = \min\{u\left(q,\overline{q},\underline{q}\right) + \epsilon\sum_{i=1}^{n} u_i(q_i,\overline{q_i},\underline{q_i}) \qquad \textbf{Eq.[19]}$$

For minimization problem, Wierzbicki(1986) defines the function u_i as

$$u_i\left(q,\overline{q},\underline{q}\right) = \begin{cases} \alpha_i w_i(\overline{q_i} - q_i) + 1, if\ q_i < \overline{q_i} \\ w_i(\overline{q_i} - q_i) + 1, if\ \overline{q_i} \leq q_i \leq \underline{q_i} \\ \beta_i w_i(\overline{q_i} - q_i), if\ \underline{q_i} \leq q_i \end{cases} \qquad \textbf{Eq.[20]}$$

With $w_i = \frac{1}{\underline{q_i} - \overline{q_i}}$

α_i, β_i being given parameters

(Makowski, 1994)Makowski (1994) uses a piece-wise linear, strictly monotone function that is interactively defined by the user via their specification of the aspiration and reservation levels ($\overline{q_i}\ and\ \underline{q_i}$), u_i of which are assigned a value of 1 and 0, respectively. If only the aspiration and reservation are indicated, the corresponding weight for criterion *i* to be used in Eq.21 is

$$w_i = \frac{1}{\left|\overline{q_i} - \underline{q_i}\right|} \qquad \textbf{Eq.[21]}$$

The user may also give additional information on their preference by indicating extra u_i value for other values of criterion *i*. Therefore, if the component achievement function of the i-th criterion has p_i segments, the function defining u_i in segment $j \in [1, p_i]$ will take the form

$$u_{ji} = \alpha_{ji} q_i + \beta_{ji}, \qquad with\ \ q_{ji} \leq q_i \leq q_{j+1,i} \qquad \textbf{Eq.[22]}$$

given that

$\alpha_{ji} = \frac{u_{j+1,i} - u_{ji}}{q_{j+1,i} - q_{ji}}$ s.t. $k > l; k, l \in [1, p_i]: \alpha_{ki} \geq \alpha_{li}$

$\beta_{ji} = u_{ji} - \alpha_{ji} q_{ji}$

A.2. THE SIMULATION MODEL

The simulation model was coded in VB.NET based on an Excel model by (Wade, 2005). It is a procedural code that calculates water supply from the River Rother, groundwater sources, the Weirwood Reservoir, and other available options to accommodate demand. The model has a simple GUI as shown in Figure A.1.

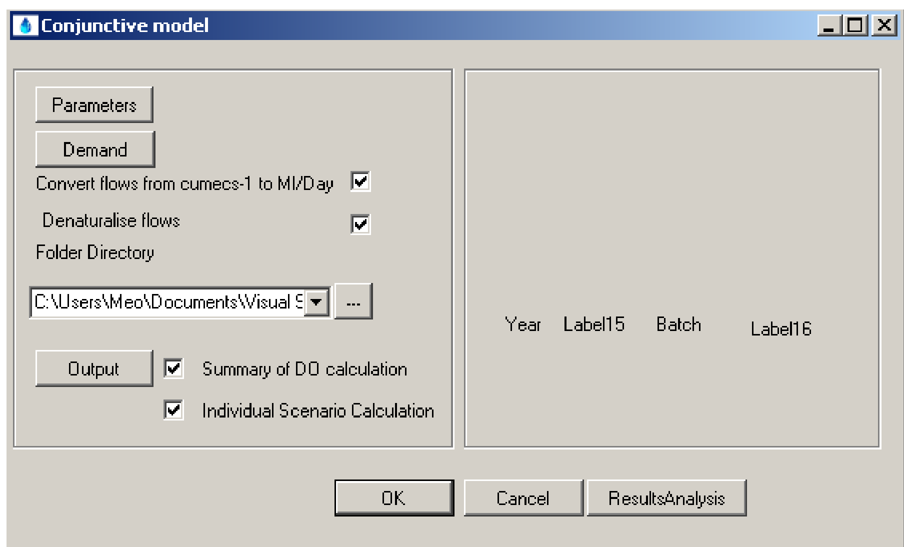

Figure A.1. GUI of the simulation model

The model loads parameters and demand time series from the csv text files and then can calculate either in batch mode or normal mode for Deployable Output (iterative search mode) and drought failures (simple simulation mode). It considers the water balance in North Sussex and then Sussex Worthing and Brighton.

A.3. SCHEMATIC OF THE AQUATOR MODEL

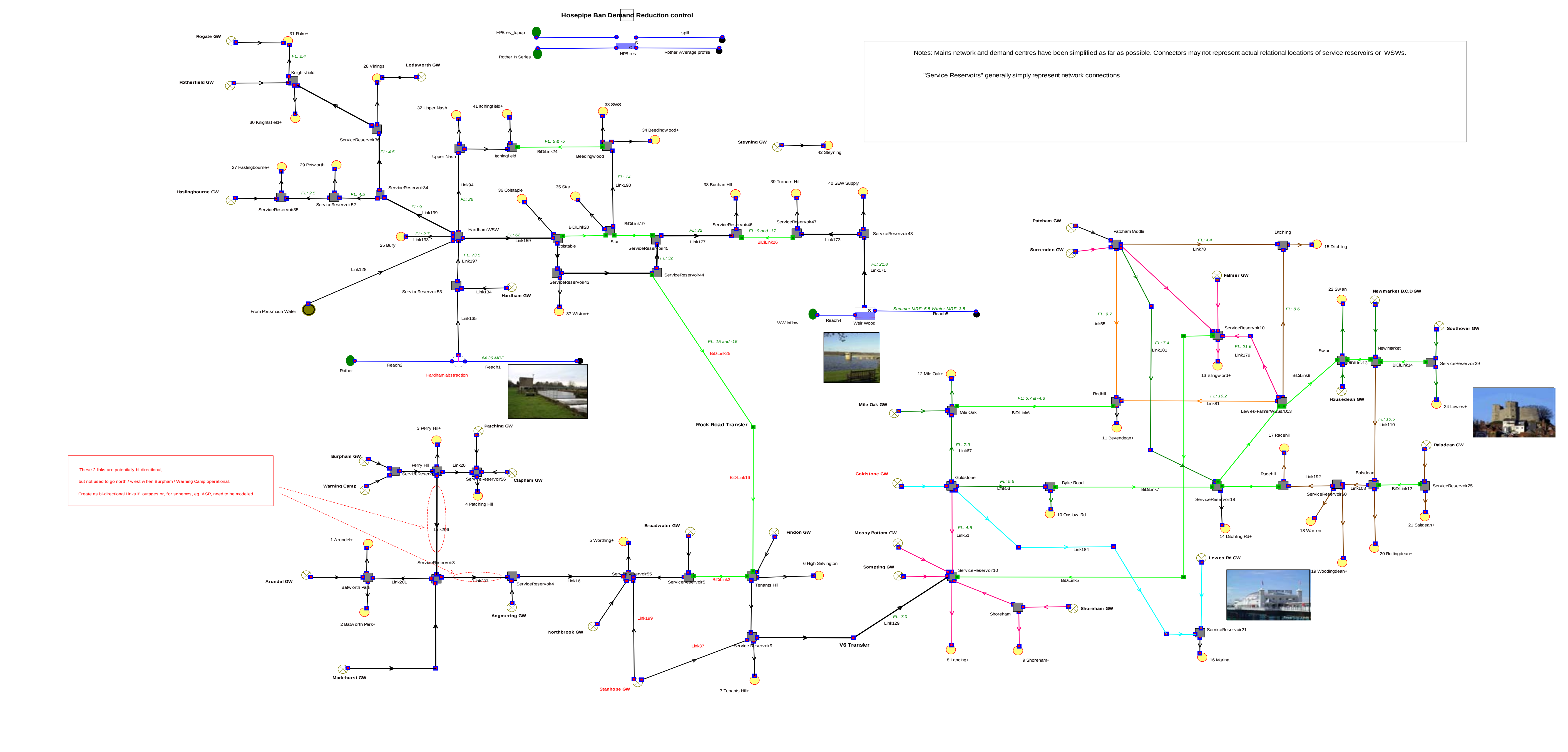

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Figure A.1. Schematic of the Aquator model

Appendix B-Model Parameters

Table B.1. List of link capacity in the Optimisation Model

Parameter Lcap(m,n)/

$ondelim

HardhamWSW	UpperValley	63
HardhamWSW	Sussex2	175
HardhamWSW	Sussex4	434
HardhamWSW	Bury	18.9
Portsmouth	HardhamWSW	99999
UpperValleyGW	UpperValley	99999
HardhamGW	Sres53	99999
Sres53	HardhamWSW	514.5
Rother	Sres53	99999
Sussex4	BuchanHill	224
Sussex4	TenantsHill	105
TenantsHill	Sussex4	105
Sussex2	Sussex3	35
Sussex3	Sussex2	35
Sussex4	Sussex3	98
BuchanHill	TurnersHill	119
TurnersHill	BuchanHill	63
SEW	TurnersHill	99999
Weirwood	SEW	152.6
Weirwood	MRFWW	99999
Rother	MRFRother	99999
TenantsHill	BrightonDem1	49
BrightonGW1	BrightonDem1	99999
ShorehamGW	Shoreham	99999
ShorehamGW	BrightonDem1	99999
BrightonDem2	BrightonDem1	99999
BrightonGW2	BrightonDem2	99999
DesalNode1	ShorehamGW	99999
DesalNode2	ShorehamGW	99999
Arun	Sres53	99999
HardhamWSW1	HardhamWSW	99999
HardhamWSW	HardhamWSW1	99999

```
HardhamWSW1          Sussex4      0.0000001
Wellfield            Sres53       99999
ASR           TenantsHill  99999
Ford          Sres53       99999
WorthingGW2   TenantsHill  99999
TenantsHill   WorthingDem  99999
WorthingGW1   WorthingDem  99999
$offdelim
/;
```

Table B.2. Cost Supply in the Optimisation and the Simulation Model

```
Parameter costSupply(n) /
$ondelim
BrightonGW1    50
BrightonGW2    50
ShorehamGW     50
HardhamGW      81
Portsmouth     250
Rother         45
UpperValleyGW  50
Weirwood       80
WorthingGW1    50
WorthingGW2    50
$offdelim
/;
```

Appendix C-The worst droughts according to each climate product in Brighton and Worthing

Table C.1 Worthing drought year-Optimisation Model

Period	Demand Profiles	RCM	FF	SCP	UKCP09
2050s	Market Forces	2040,2054,2056, 2058,2061,2062, 2066,2069	2040,2043,2045, 2048,2050,2052, 2053,2056,2063, 2066	1970,1976, 1977,1978, 1984,1985, 1988	1961,1969,1975, 1976,1977,1984, 1988,1989,1990
2050s	Local Resilience	2040,2057, 2058,2060, 2062,2066, 2067	2042,2046,2054, 2057,2058,2062, 2064,2066	NA	NA

Table C.2 Worthing drought year-Simulation Model

Period	Demand Profiles	RCM	FF	SCP	UKCP09
2050s	Market Forces	2040,2041,2042	2040,2041,2042	1962	1961,1962,1963,1967

Table C.3 Brighton drought year-Optimisation Model

Period	Demand Profiles	RCM	FF	SCP	UKCP09
2050s	Market Forces	2040,2043, 2051,2053, 2055,2061, 2063,2065, 2067	2040,2041, 2044,2046, 2051,2054, 2056,2058, 2060,2061	1963,1967, 1975,1976, 1978,1983, 1988,1989, 1990	1961,1962,1963,1964, 1965,1966,1967,1968, 1969,1973,1974,1975, 1976,1977,1978,1979, 1980,1981,1982,1983, 1984,1985,1986,1987, 1988,1989,1990
2050s	Local Resilience	2040,2041, 2044,2057,	2040,2041, 2047,2054,	1961,1976	1961,1976, 1989

	2060,2066, 2067	2057,2058, 2065,2067, 2068

Table C.4 Brighton drought year-Simulation Model

Period	Demand Profiles	RCM	FF	SCP	UKCP09
2050s	Market Forces	2040	2040	1962	1962
2050s	Local Resilience	2040	2040	1961	1961

Glossary

Adaptability	The ability, competency or capacity of a system to adapt to (to alter to better suit) climatic stimuli
Adaptation	Adjustments in human systems to changes in climatic stimuli
Adaptive Capacity	The potential or capability of a system to adapt to (to alter to better suit) climatic stimuli. An adaptation characteristic
Anticipatory adaptation	Actions before observed impacts of changes or proactive adaptation
Aquator	A water resource model that can simulate and optimise the water supply-demand balance at a daily time step
Autonomous adaptation	Passive and spontaneous adaptation to existing changes
'Bottom-up' approach	The approach constructs based on the available adaptive capacity and resources- the limiting factors of possible adaptation actions
CATCHMOD	A lumped hydrological model used by the Environment Agency and several water companies. The model uses rainfall and evapotranspiration (PET) inputs to simulate surface, subsurface flows and groundwater level
Classical Robustness	The classical robustness emphasises trade-offs between cost and system performance, and at the same time requires low-regret for the selected decision
Climate Post-processing	The process of converting climate model outputs into products and information of suitable format, variables and temporal/spatial scales to the users' need
Coping Capacity	Degree to which a system can successfully grapple with a stimulus (similar to adaptability, but includes more than adaptive means of "grappling")
Decision-Scaling	A methodology by Brown (2010) to explore the climate sensitivities of a system or decision and then tailor climate

	information to assist decision making
Deep uncertainty	A situation in which analysts do not know or cannot agree on (1) models that relate key forces that shape the future, (2) probability distributions of key variables and parameters in these models, and/or (3) the value of alternative outcomes
Demand management	Measures in which the company uses short and long-term strategies to increase water use efficiency and reduce water consumption
Deployable Outputs	The demand that can be met without violating constraints and causing the system to fail
Ecological adaptation	The reactive responses and genetic evolution of a species
Effectiveness	The capacity of an adaptation action to achieve its expressed objectives
Efficiency	Consideration of the distribution of the costs and benefits of the actions; the costs and benefits of changes in those goods that cannot be expressed in market values; and the timing on adaptation actions
Equifinality	The notion that different model structures and parameterisation can produce an acceptable model performance
Equity	Identifying who gains and who loses from any impact or adaptation policy decision. An adaptation characteristic
Flexibility	Degree to which a system is pliable or compliant (similar to adaptability, but more absolute than relative). An adaptation characteristic
Fuzzy Robustness	This is an extension of classical set-based robustness, with the improvements being the usage of likelihood/membership function and a more flexible definition of system failures. It compares the risk of system failure after and before a decision by examining the overlapping region between the operating system state (e.g. water supplies) and the failure region (or region of high risks)
Generalised Likelihood Uncertainty Estimation	A framework by Beven and Binley (1992) that explores possible outcomes via a group of behavioural models instead of a single

(GLUE)	calibrated and validated model.
HadRM3 climate model	A regional climate model of the Hadley Centre, at the UK Meteorological Office
Headroom	The planned extra water supply capacity to accommodate demand uncertainty
Impact Potential	Degree to which a system is sensitive or susceptible to climate stimuli
Info-gap Decision Theory	A methodology that explores the deterioration of strategy performance as system parameters or descriptions deviate from "best estimates", provided by expert judgment or nominal description
Innovation (I)	A socio-economic scenario in which total water demand reduces by 4%, water per capita consumption (pcc) 125 l/d/capita. The responsibility to find adaptation strategies lies with the government and scientist; demand reduction is due to sustainability-led governance and technological innovation.
Legitimacy	The extent to which decisions are acceptable to participants and non-participants that are affected by those decisions
Local Resilience (LR)	A socio-economic scenario in which total water demand increases by 8%; pcc is 140 l/d/capita. People realise the need for demand reduction and take actions towards it. Their efforts, however, are moderate due to the low priority of demand saving and the lack of incentives from the government.
Market Forces (MF)	A socio-economic scenario in which total water demand increases by 35%, pcc 165 l/d/capita. Water demand is driven by the market trend, focusing on cost optimisation and growth.
Palmer Drought Severity Index (PDSI)	A soil moisture/water balance model that cumulatively measures surface water balance, thus capable of indicating meteorological and hydrological droughts
Real options analysis	A decision technique that focuses explicitly on the sequential nature of decision making, concerns future options and actively plans for the prospect of new options
Resilience	Degree to which a system rebounds, recoups or recovers from a

	stimulus/ the capacity to regain system functions after disturbance
Resistance	Degree to which a system opposes or prevents an effect of a stimulus
Responsiveness	Degree to which a system reacts to stimuli (broader than coping ability because responses need not be "successful")
Robust Decision Making (RDM)	The approach that uses sets of scenarios to explore plausible futures, emphasise adaptability as a central attribute, and search iteratively for conditions. It focuses on characterising vulnerabilities of the system under a large ensembles of scenarios and interacts with the decision makers to identify and assess options for vulnerability reduction.
Robustness	The system capacity to resist disturbances while maintaining planning flexibility amidst uncertainty
Sensitivity	Degree to which a system is affected by, or responsive to, climate stimuli
Stability	Degree to which a system is not easily moved or modified. An adaptation characteristic
Standardised Precipitation Index	The index that presents droughts as precipitation deficit over multiple timescales. It a modified version of the SPI, using a simplified moisture balance of rainfall and PET
Statistical Robustness	The possibility of an option being optimal over all other options
Supply management	Decisions in which the water company seeks extra supply sources via new constructions of water storage/abstraction infrastructure or other transfer contracts with neighbouring water companies.
Susceptibility	Degree to which a system is open, liable or sensitive to climate stimuli (similar to sensitivity, with some connotations toward damage)
Sustainable Behaviour (SB)	A socio-economic scenario in which the total water demand declines by 15% due to pro-active demand reduction from individuals; pcc is 110 l/d/capita.
'Top-down' approach	The approach that designs adaptation policy to alleviate the vulnerabilities exposed by climate uncertainty

Unsatisfactory State	The state occurs when the system displays characteristics outside of the decision makers' desired range
Vulnerability	Degree to which a system is susceptible to injury, damage, or harm
Water Resource Management Plan	The 5-yearly water resource management plan on a 25-year horizon produced by water companies in England and Wales