

CRANFIELD UNIVERSITY

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COPING WITH CLIMATE CHANGE UNCERTAINTY FOR
ADAPTATION PLANNING FOR LOCAL WATER MANAGEMENT

SCHOOL OF APPLIED SCIENCE
Water Sciences Institute

PhD
Academic Year: 2010 - 2014

Supervisor: Professor Keith Weatherhead
May 2014

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ABSTRACT

Environmental management is plagued with uncertainty, despite this, little attention has until recently been given to the sensitivity of management decisions to uncertain environmental projections. Assuming that the future climate is stationary is no longer considered valid, nor is using a single or small number of potentially incorrect projections to inform decisions. Instead, it is recommended that decision makers make use of increasingly available probabilistic projections of future climate change, such as those from perturbed physics ensembles like United Kingdom Climate Projections 2009 (UKCP09), to gauge the severity and extent of future impacts and ultimately prepare more robust solutions.

Two case studies focussing on contrasting aspects of local water management; namely irrigation demand and urban drainage management, were used to evaluate current approaches and develop recommendations and improved methods of using probabilistic projections to support decision making for climate change adaptation. A quantitative understanding of the impact of uncertainty to decision making for climate change adaptation was obtained from a literature review; followed by a comparison of using (1) the low medium and high emission scenarios, (2) 10,000 sample ensemble and 11 Spatially Coherent Projections (11SCP), (3) deterministic and probabilistic climate change projections, (4) the complete probabilistic dataset and sub-samples of it using different sampling techniques, (5) the change factor (or delta change) and stochastic (or UKCP09 weather generator) downscaling techniques and (6) different decision criteria using two contrasting case studies at three UK sites.

This research provides an insight into the impact of different sources of uncertainty to real-world adaptation and explores whether having access to more data and a greater appreciation of uncertainty alters the way we make decisions. The impact of the “envelope of uncertainty” to decision making is explored in order to identify those factors and decisions that have the greatest impact on what we perceive to be the “best” solution. An improved novel decision criterion for use with probabilistic projections for adaptation planning is presented and tested using simplified real-world case studies to establish whether it provides a more

attractive tool for decision makers compared to the current decision criteria which have been advocated for adaptation planning.

This criterion explicitly incorporates the unique risk appetite of the individual into the decision making process, acknowledging that this source of uncertainty and not necessarily the climate change projections, had the greatest impact on the decisions considered by this research. This research found the differences between emission scenarios, projection datasets, sub-sampling approaches and downscaling techniques, each contributing a different source of uncertainty, tended to be small except where the decision maker already exhibited an extremely risk seeking or risk adverse appetite. This research raises a number of interesting questions about the “decision significance” of uncertainty through the systematic analysis of several different sources of uncertainty on two contrasting local water management case studies. Through this research, decision makers are encouraged to take a more active role in the climate change adaptation debate, undertaking their own analysis with the support of the scientific community in order to highlight those uncertainties that have significant implications for real world decisions and thereby help direct future efforts to characterise and reduce them. The findings of this research are of interest to planners, engineers, stakeholders and adaptation planning generally.

Keywords:

Climate change, adaptation planning, UKC09, irrigation reservoir, SUDS

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LIST OF ABBREVIATIONS

11RCM	11 Regional Climate Models
11SCP	11 Spatially Coherent Projections
BADC	British Atmospheric Data Centre
BMP	Best Management Practice
CAPEX	Capital Expenditure
CBA	Cost Benefit Analysis
CF	Change Factor
DEFRA	Department of Environment, Food and Rural Affairs
EA	Environment Agency
EPSRC	Engineering and Physical Sciences Research Council
ETo	Reference Evapotranspiration
FEH	Flood Estimation Handbook
GCM	General Circulation Model
GHG	Greenhouse Gases
IH124	Institute of Hydrology Report 124
IPCC	Intergovernmental Panel on Climate Change
LHS	Latin Hypercube Sampling
LoS	Level of Service
MAUT	Multi-Attribute Utility Theory
MAX LHS	Maximin Latin Hypercube Sampling
MCA	Multi-Criteria Analysis
MIDAS	Met Office Integrated Data Archive System
NPV	Net Present Value
NRI	Normalised Relative Impact
OPEX	Operational Expenditure
OPT LHS	Optimum Latin Hypercube Sampling
PP	Probabilistic Projections
PRD	Partial Root-zone Drying
RCM	Regional Climate Model
RDI	Regulated deficit irrigation
ReFH	Revitalised Flood Hydrograph
SAB	SUDS Approving Body

SCS	Soil Conservation Service
SEPA	Scottish Environmental Protection Agency
SfA7	Sewers for Adoption 7 th edition
SRS	Simple Random Sampling
SUDS	Sustainable Urban Drainage Systems
TD	Traditional Drainage
TRRL	Transport and Road Research Laboratory
UHIE	Urban Heat Island Effect
UK	United Kingdom
UKCIP	United Kingdom Climate Impacts Programme
UKCP09	United Kingdom Climate Change Projections 2009
WFD	Water Framework Directive
WG	Weather generator

CHAPTER 1. INTRODUCTION

1.1 Overview

This chapter begins by providing an overview of the background of the research undertaken, outlining the research question, aim, objectives and novel contribution of this research. The remaining chapters of the thesis are summarised along with a thesis diagram to help guide readers. A list of the submitted/published papers is also provided.

1.2 Background

Adaptation refers to any action, tangible or otherwise, designed to moderate potential damages or to benefit from opportunities created by future climate change (Smit and Wandel, 2006). Stakeholders face many challenges in preparing, prioritising and implementing adaptation plans designed to cope with future climate change and its potential impacts. Despite information on the benefits of climate change adaptation planning being widely available and well documented (Füssel, 2007; Ranger et al., 2010; Harris et al., 2012), in the UK at least, it is reported that until recently relatively few real world cases of climate change adaptation planning had been recorded outside of government-led initiatives (Tompkins et al., 2010; Wilby and Dessai, 2010). Elsewhere in the world while adaptation has been recorded it has seldom been undertaken in response to climate change alone and is often viewed as inadequate (Adger et al., 2009; Berrang-Ford et al., 2011). Working group II of the IPCC in their summary to policy makers which was released in March of 2014 suggest that there is high confidence that adaptation is beginning to embed itself within existing planning processes, with emerging evidence of some limited implementation of responses (IPCC, 2014). The IPCC are very confident that adaptation experience is beginning to accumulate across regions in the public and private sector and within communities. There is some evidence that governments at various levels are beginning to integrate adaptation plans and policies with existing development plans. The existing evidence and scientific consensus seem to suggest that adaptation has until now, emphasised

incremental adjustments and co benefits, although there is emerging evidence of emphasis on flexibility and learning (IPCC, 2014). There is a strong scientific consensus that most adaptation assessments to date, have tended to focus on impacts, vulnerability and adaptation planning and very few have focussed on the process of implementation and the effects of adaptation (IPCC, 2014). Limited uptake of adaptation has been attributed to a variety of factors including the vast uncertainties, the lack of investment in adaptation planning and arguably the lack of probabilities assigned to the current generation of climate change projections, thereby limiting the usefulness of traditional decision criteria and methods (see Moser and Ekstrom, 2010 for a more extensive list). The lack of guidance on this issue has hampered decision making as adaptation options tend to be difficult to compare to each other in a quantitative manner, complicating their design and eventual implementation (Lecocq and Shalizi, 2007). The move from deterministic to probabilistic methods of communicating climate change information observed in recent years, driven by improvements in uncertainty quantification (Rougier, 2007; Stainforth et al., 2007; Tebaldi and Knutti, 2007), has further complicated matters by communicating extra uncertainty within the projections that was previously not available to decision makers, who may have limited experience working with uncertainty.

Robust adaptation is partly dependent on the availability of and access to salient, credible and legitimate climate change information (Tang and Dessai, 2012). With increasing access to and availability of climate change information and more recently probabilistic climate change projections in the UK, in the form of United Kingdom Climate Projections 2009 (UKCP09) (Murphy et al., 2009), we are now better equipped to engage in adaptation planning. However, current approaches to decision making for adaptation planning have been criticised for being data demanding, too restrictive, overly complex, and crude (French, 1986; Etner et al., 2012; Knight, 2012). Some cannot be used with sub-samples of the UKCP09 dataset, often a practical necessity for working with such a large dataset (Christierson et al., 2012).

1.3 Research question, aim and objectives

The research question ‘what are the advantages, disadvantages and implications of using probabilistic projections for decision making for adaptation planning for local water management in the UK?’ was posed in response to the recognised knowledge gap that was identified and is discussed in more detail in CHAPTER 2.

In summary, water is recognised as the primary medium through which most people will experience the effects of climate change (Stakhiv, 2011). The most apparent and commonly cited threats being increased risk of flooding and greater change of drought in certain areas. In response to these threats most adaptation that has taken place to date, has been local scale in its implementation due to the complexities and uncertainties associated with preparing and implementing effective regional/national adaptation. In order to explore the impact of using probabilistic projections for decision making for adaptation planning for local water management it was necessary to focus on two contrasting and complementary case studies, namely irrigation demand management and urban drainage, discussed in more detail in CHAPTER 4. These case studies on the surface appear contrasting, but on further investigation are in fact a product of the same problem, that is how we manage environmental uncertainty to ensure robust adaptation, the focus of this research.

The aim of this research was to ‘evaluate current approaches and develop recommendations and improved methods for using probabilistic projections to support decision making for climate change adaptation planning, with a focus on local water management’. To achieve this stated aim, research objectives (1-3) and sub objective (2.1-2.5) were devised.

Objective 1 Explore how stakeholders can use probabilistic projections to support climate change adaptation planning and explore current motivation and uptake barriers to adaptation.

Objective 2 Critically evaluate current methods of using probabilistic projections for climate change adaptation planning with a focus on local water management.

Sub-objective 2.1 Critically compare scenario-led and vulnerability-led approaches to climate change adaptation.

Sub-objective 2.2 Critically compare the 11SCP and the 10,000 sample ensemble datasets. Establish whether these datasets would yield different decision outcomes and explore the implications of using probabilistic projections in place of non-probabilistic (deterministic) projections.

Sub-objective 2.3 Establish whether sub-sampling the probabilistic projections is appropriate, establish whether different decision outcomes would arise if sub samples were used in place of the complete dataset and explore the implications of using advanced stratified sampling methods (LHS) over simple random sampling methods.

Sub-objective 2.4 Critically compare the change factor (delta factor) and stochastic (UKCP09 weather generator) downscaling techniques. Establish whether these downscaling techniques would yield different decision outcomes to each other and explore the implications of using one approach over the other.

Sub objective 2.5 Critically compare decision criteria using probabilistic climate projections for adaptation planning, establish whether these criteria would yield different decision outcomes to each other and explore the implications of using one approach over the other.

Objective 3 Develop recommendations and improved methods for using probabilistic projections for climate change adaptation planning.

1.4 Research contribution

The novel contributions of this research to the topic area are as follows:

1. **A quantitative understanding of the impact and sensitivity of uncertainty to decision making for adaptation planning for local water management** was obtained from a literature review; followed by a comparison of using (1) the low medium and high emission scenarios, (2) 10,000 sample ensemble and 11SCP, (3) deterministic and probabilistic climate change projections, (4) the complete probabilistic dataset and sub-samples of it (using different sampling techniques), (5) the change factor (delta change) and stochastic (UKCP09 weather generator) downscaling techniques and (6) different decision criteria with two distinct and contrasting case studies at three UK sites.
2. **A novel decision criterion and accompanying framework to support adaptation planning** was developed to identify robust decision outcomes in situations of uncertainty “in which analysts do not know or the parties to a decision cannot agree upon (1) the appropriate models to describe interactions among a system’s variables, (2) the probability distributions to represent uncertainty about key parameters in the models, and/or (3) how to value the desirability of alternative outcomes” (Walker et al., 2013, p.958).

1.5 Thesis structure

A graphical overview and summary description of each chapter is provided in Figure 1.1, each addressing a particular source of uncertainty from using probabilistic climate change projections to support adaptation planning, the combined assessment of which formed the basis of the novel decision criterion presented here.

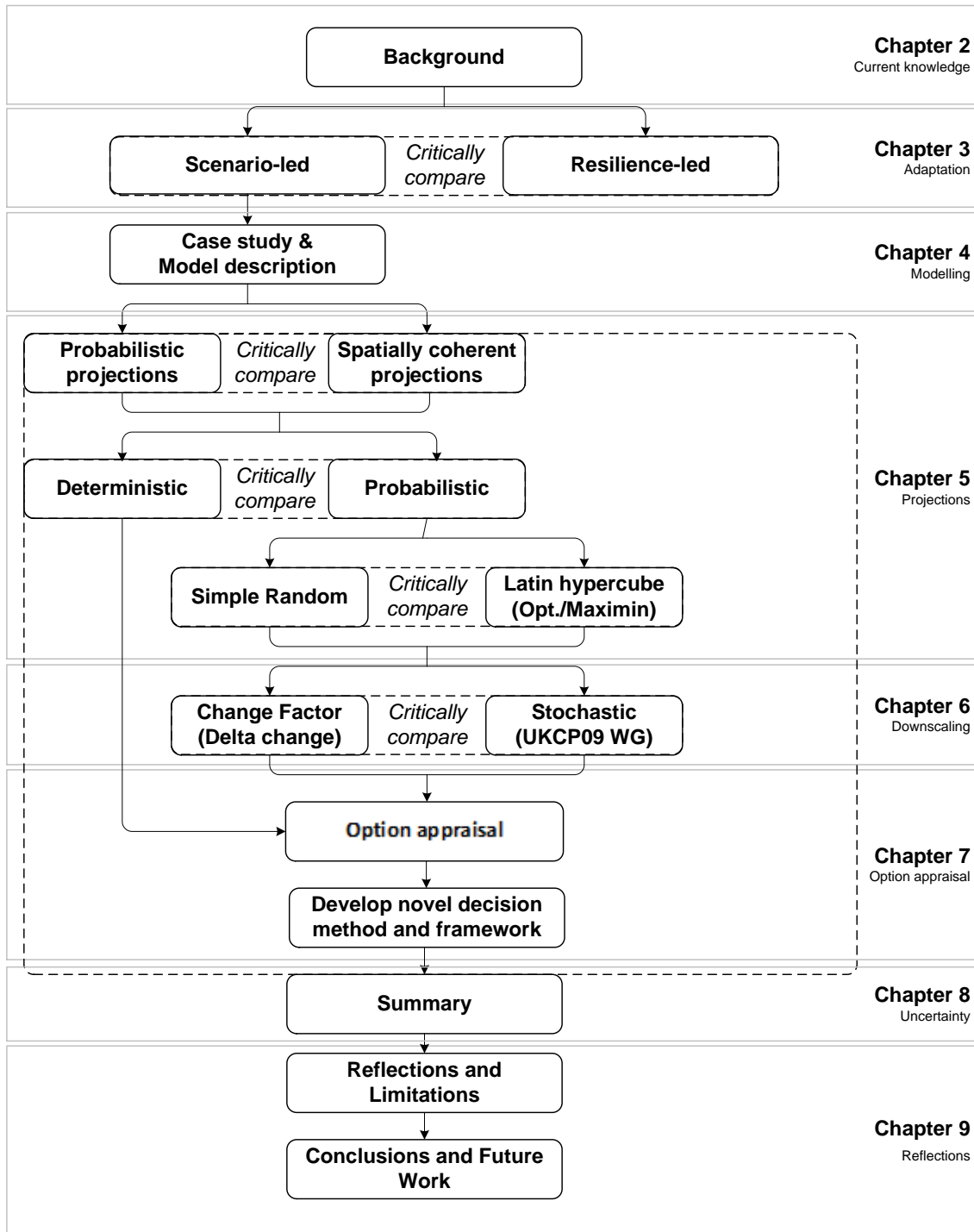


Figure 1.1 Thesis structure

Chapter 2: Current Knowledge

Direct and indirect climate change impacts and their implications for water resources are identified, approaches to climate risk management and adaptation are outlined and what constitutes ‘good’ adaptation practice is

explored. UKCP09, probabilistic projections and different downscaling techniques are discussed. A selection of decision criteria typically employed in situations of strict uncertainty are introduced. The scenarios underpinning this research are described. The knowledge gap underpinning this research is also identified and discussed.

Chapter 3: Adaptation: Scenario-led (top down) and Vulnerability-led (bottom-up) Adaptation

The barriers and motivation for adaptation planning are discussed. The merits and limitations of scenario-led (top down), vulnerability led (bottom-up) and hybrids thereof are discussed.

Chapter 4: Modelling: Irrigation Demand and Urban Runoff

The case studies, sites, model, cost benefit analysis and assumptions underpinning the research, together with their justification are described.

Chapter 5: Projections: A Systematic Comparison

An extended literature review discussing the merits and limitations of the 11SCP and 10,000 sample ensemble, deterministic and probabilistic climate change projections, simple random and Latin hypercube sampling versus using the complete probabilistic dataset is provided. Research methods and accompanying rationale are provided. Results for two case studies at three UK sites using all three emission scenarios for the 2050s are summarised.

Chapter 6: Downscaling: Change Factor (Delta Change) and Stochastic (UKCP09 Weather Generator)

An extended literature review discussing the merits and limitations of change factor (delta change) downscaling using 10,000 member ensemble and stochastic (UKCP09 weather generator) downscaling. Research methods and accompanying rationale are provided. Results for two case studies at three UK sites using all three emission scenarios for the 2050s are summarised.

Chapter 7: Option appraisal: Decision making under uncertainty

The merits and limitations of current decision criteria and methods under uncertainty are discussed. A novel decision criterion and accompanying framework is outlined. A critical review of this novel decision criterion is provided, its contribution to decision making is discussed. Results for two case studies at three UK sites using all three emission scenarios for the 2050s are summarised.

Chapter 8: Uncertainty: A Summary

The impact of uncertainty to decision making for local water management is summarised. Results for two case studies at three UK sites using all three emission scenarios for the 2050s are summarised.

Chapter 9: Reflections: Discussion and Conclusions

A summary response to the original research question, limitations, novel contribution of this research and summary conclusions for each research objective is provided. Areas of further work are also summarised.

1.6 Papers

- Green, M and Weatherhead, E. K., (2014d), "The application of probabilistic climate change projections: A comparison of methods of handling uncertainty applied to UK irrigation reservoir design", *Journal of Water and Climate Change*, In Press.
- Green, M and Weatherhead, E. K., (2014c), "Coping with climate change uncertainty for adaptation planning: An improved criterion for decision making under uncertainty using UKCP09", *Climate Risk Management*, vol. 1, pp. 63-75.
- Green, M. and Weatherhead, E. K., (2014b), "A critical comparison of using a probabilistic weather generator versus a change factor approach; irrigation reservoir planning under climate change", *Journal of Water and Climate Change*, vol. 5, no. 10, pp. 13-24.

- Green, M and Weatherhead, E. K., (2014a), "Irrigation demand modelling using the UKCP09 weather generator: lessons learned", *Journal of Water and Climate Change*, In Press doi:10.2166/wcc.2013.052

CHAPTER 2. CURRENT KNOWLEDGE

2.1 Overview

The chapter begins by identifying direct and indirect impacts associated with future climate change and explores their implications for water resources. Next, two contrasting approaches to climate risk management, namely mitigation and adaptation are introduced, followed by a short discussion of the different types of adaptation. The United Kingdom Climate Impacts Programme (UKCIP), UKCP09 and probabilistic projections are introduced and different downscaling techniques are discussed. A selection of decision criteria typically employed in situations of strict uncertainty are introduced. The scenarios underpinning this research are described. Finally, the knowledge gap underpinning this research is identified and discussed in the context of the wider reviewed literature.

2.2 Background

2.2.1 Introduction

In the United Kingdom (UK), infrastructure providers are required under government reporting powers to review the potential impact of climate change on their assets and service delivery (Parliament, 2008), similar policies are now in place in other parts of the world including the US. The UK reporting powers reflect a growing national concern about the potential impacts of climate change and its implications on the resilience and management of 'long-lived' assets (Brown and Wilby, 2012). It could be argued that analysing climate risks is a matter of due diligence, given the potential impacts and the overwhelming evidence that recent climate change is attributable to anthropogenic activity (IPCC, 2013). However at present, no scientific consensus exists regarding the best methods to use to evaluate the risks of climate change and implement adaptation (Brown and Wilby, 2012).

2.2.2 Climate change

"Warming of the climate system is unequivocal, and since the 1950s, many of the observed changes are unprecedented over decades to millennia. The

atmosphere and ocean have warmed, the amounts of snow and ice have diminished, sea, level has risen, and concentration of greenhouse gases (GHG) has increased” (IPCC, 2013, p.2).

Globally average combined land and surface temperature data shows that a warming of 0.85°C (0.65 - 1.06°C) occurred during the period 1880 to 2012. The longest dataset currently available shows that the total average temperature increase between 1850-1900 and 2003-2012 period was 0.78°C (IPCC, 2013). Since 1850, the last three decades have been progressively warmer at the Earth’s surface than any other proceeding decades. In addition, the Intergovernmental Panel on Climate Change (IPCC) has medium confidence that in the Northern Hemisphere, the 30 year period between 1983 - 2012 was likely the warmest period in the past 1400 years (IPCC, 2013).

The IPCC are “virtually certain” that the upper ocean (0-700m) warmed between 1971 to 2010, while they are “likely certain” that the upper ocean warmed between the 1870s and 1971 (IPCC, 2013). Globally, the largest warming has occurred near the surface, an increase of 0.11°C (0.09 – 0.13°C) occurred per decade during the period 1971 - 2010 in the upper 75 m (IPCC, 2013).

In the last two decades, the Greenland and Antarctic ice sheets have continued to lose mass, simultaneously glaciers have shrunk across the globe, while arctic sea ice and Northern hemisphere snow cover has decreased in its extent (IPCC, 2013).

Atmospheric concentrations of carbon dioxide and nitrous oxides have increased to unprecedented levels in the last 800,000 years. Since pre-industrial times, concentrations have increased by approximately 40%, largely the result of fossil fuel emissions and changes in land use. The ocean is believed to have absorbed 30% of anthropogenic carbon dioxide emissions leading to ocean acidification (IPCC, 2013).

Since 1950, changes in many extreme water and climate events have been observed. The IPCC state that it is very likely that the number of cold days and nights have decreased on a global scale, simultaneously, the frequency of heat

waves has increased in parts of Europe, Asia and Australia. It is likely that more regions exist where the number of heavy precipitation events have increased than regions where the number of events where it has decreased (IPCC, 2013). In North America and Europe, the frequency or intensity of heavy precipitation events has likely increased. In other countries, the IPCC has stated that there is medium confidence that changes in heavy precipitation events have been observed (IPCC, 2013).

In summary, the relentless pursuit of energy by society has contributed in part to changes in atmospheric composition, a build-up of GHG in the lower atmosphere, acidification of the Earth's oceans and rising regional and global temperatures (Harris et al., 2012). The impacts of climate change on regional precipitation are however less certain (Howard et al., 2010). Though water is believed to be the primary medium through which people, ecosystems and economies will experience the effects of climate change (Stakhiv, 2011) with significant implications for sustainable development, economic growth and poverty reduction efforts, as well as wider implications for a variety of sectors including food, energy, conservation and health (Stakhiv and Stewart, 2010).

Climate change has the potential to profoundly change the natural and social environment (Mitchell and Jones, 2005). Freshwater resources across much of the Earth's surface are expected to be placed at increased risk, in part due to current infrastructure being ill-equipped to handle future climate change. Much of our current infrastructure was built on the assumption that the climate during which it was built would remain the same for its entire lifetime – this is no longer the case (Harris et al., 2012). Changes in seasonal and interannual climate can have significant implications for agricultural production, water resources and terrestrial and marine ecosystems (Räisänen and Ruokolainen, 2006; Santoso et al., 2008; Stakhiv and Stewart, 2010). Climate change has the potential to increase the risk of flooding, reshape supply and demand patterns and has the potential to disturb and contaminate water resources with significant implications for a variety of sectors (Hulme et al., 2002). Some studies suggest that a warming climate could increase the atmosphere's water holding capacity, leading to

intensification of the hydrological cycle and potentially increase the amount of renewable fresh water resources available in the future (Allen and Ingram, 2002; Berg et al., 2009). Other studies founded on complex radiative balance models have suggested that a decrease in precipitation in non-convective regions, attributed to an intensification of seasonal cycles in conjunction with an increase in the magnitude and frequency of extreme events has the potential to increase the vulnerability of human communities (Trenberth et al., 2003; Allan and Soden, 2007).

In the context of climate change, two categories of risk have been suggested. The first category encompasses direct and indirect risks posed by climate change, with potentially damaging and disastrous though uncertain outcomes for both humanity and ecosystems (Froyn, 2005). The second category of risk is associated with the concept of maladaptation. Maladaptation can result in increased vulnerability and is especially common of options with long lifespans or that are exposed to deeply uncertain conditions. Various types of maladaptation exist including “avoidable” maladaptation which arises from a poor *ex ante* choice where information is used incorrectly (IPCC, 2014b). “Unavoidable” *ex post* adaptation can occur in situations where the appropriate decisions were made based on the best available information at the time, but this information then later proves to be wrong (IPCC, 2014b). This is by no means an exhaustive list of maladaptation, which can take many forms and have varying impacts. For example development policies and actions which focus on short term gains may offer immediate benefits but later result in medium to long term impacts. Such examples of maladaptation are common of “hard” infrastructure, which can reduce the flexibility and range of adaptation options which are available in the future (Adger et al., 2003; Eriksen and Kelly, 2007, OECD, 2009). Similarly adaptation in one area may inadvertently lead to increased vulnerability in another area, this type of maladaptation is particular common in hydrological systems where solutions at one end of the system e.g. armouring of a coastline, building of levees etc. can have adverse impacts at another end of the system (IPCC, 2014b). Furthermore these “hard” solutions are often accompanied by unwanted development often motivated by an “exaggerated sense of safety”

(Grothmann and Patt, 2005; National Research Council, 2010; Repetto, 2008). Individuals and organisations engaging in adaptation could be seen as ‘wasting’ a large amount of money on measures designed to mitigate potential impacts that may be less severe or never actually occur. The very notion of maladaptation and its negative connotations means many stakeholders are hesitant about investing in costly adaptation schemes, which may take decades for their full benefits to be felt.

2.2.3 Mitigation and Adaptation

Two distinct approaches to climate risk management have emerged in response to the risks posed by anthropogenic climate change, namely mitigation and more recently adaptation, though itself not a new phenomenon. Mitigation refers to an anthropogenic intervention to reduce the sources or enhance the sinks of greenhouse gases (Parry, 2007). In contrast, adaptation refers to “the adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects which moderates harm or exploits beneficial opportunities” (Parry, 2007, p.6). Adaptation to environmental changes has occurred through human history, although in recent years it has received much greater attention as societies begin to acknowledge anthropogenic climate change and their exposure to its associated impacts (Wilby and Keenan, 2012). In the UK, adaptation planning emerged as a policy issue in 1997 in response to the formulation of UKCIP, receiving renewed interest with the passing of the Climate Change Act 2008 (Hedger et al., 2006; Tang and Dessai, 2012). Climate change mitigation targets the root cause of anthropogenic climate change as opposed to dampening the severity of its symptoms (Rahman et al., 2007; Bartlett et al., 2009). Unfortunately to date current mitigation targets have largely gone unfulfilled. The apparent failing of global mitigation efforts such as the Kyoto protocol (Anderson and Bows, 2011; Fung et al., 2011; Sanderson et al., 2011) has led to a surge in interest in climate change adaptation, partly driven by stakeholders seeking to better manage their own resources, particularly water. Water management and governance needs to address both short-term and long term issues associated with natural climate variability and shifts imposed by climate change (Clarvis et

al, 2013). Although it is generally accepted that more must be done to integrate stochastic climate variability, opinion is currently divided on how to integrate uncertain climate change impacts (Stakhiv, 2011; Steinschneider and Brown, 2013).

Decision makers must have an understanding of how their resources, are likely to change in the future in order to better anticipate and ultimately adapt to the potential impacts of climate change (Santoso et al., 2008; Sharma and Gosain, 2010). For example, a recent study combining product-based water volume estimates, economic and climate model information suggests that 31% of total UK imports by value, including commodities such as rice, bovine and pig meat production, plastics and paper, could be placed at significant risk due to their combined dependencies on about 12.8 billion m³ of embodied water (Hunt et al., 2014). Failure to account for future climate change may lead to significant costs retrofitting or even replacing assets and may even result in decision makers overlooking lucrative opportunities associated with future climate change. Encouraging greater water efficiency is an important foundation of climate change adaptation. Flooding and its impacts in particular and its implications has been cited as a significant driver of climate change adaptation (Tompkins et al., 2010).

While adaptation continues to receive growing support within the scientific community and what constitutes adaptation is now clearly defined and understood (Adger et al., 2005), few documented cases of adaptation have been realised (Wilby and Dessai, 2010; Ford et al., 2011). Evidence is however beginning to emerge that shows that adaptation is starting to take place albeit slowly. Until now, adaptation has been largely dominated by government initiatives, principally in the form of research into climate change impacts as well as low cost low effort solutions and low regret strategies (Tompkins et al., 2010). For example in response to the rising threat of severe floods, the Scottish Environment Protection Agency (SEPA) has invested in Sustainable Urban Drainage Systems (SUDS) to improve road drainage (Tompkins et al., 2010). New supply-side and demand management measures have emerged within the

water resource management sectors, driven by projected changes in population, economic change, water availability due to altered environmental regulations and climate change (Arnell and Delaney, 2006). In the UK, the vast majority of adaptation has taken place within the public sector, signs are beginning to emerge in the private sector that it is beginning to take place (Tompkins et al., 2010). Examples have been highlighted to suggest that the private sector have been subtly and not so subtly pressuring the government to mainstream adaptation within the existing planning processes (Tompkins et al., 2010). The Association of British Insurers produced a report in 2005 criticising the Governments plans to build 200,000 new dwellings in existing flood plains in the Southeast of England, the report directly cited the increased risks posed by climate change to flooding as the main reasons (Association of British Insurers, 2005).

Despite the considerable uncertainty and limited action, it could be argued that the UK as a global industry leader and a key contributor of GHG to the atmosphere has an 'ethical obligation' to develop techniques and tools for supporting climate change adaptation planning which can be applied to other areas of the world which are at greater risk (Harris et al., 2012). Compared to other countries, climate change impacts in the UK are expected to be less severe. However, water supplies are highly sensitive and may potentially undergo large changes and generate substantial risks in response to subtle changes in the climate (Gleick, 2011). The unpredictability of the future climate change is perhaps one of the greatest challenges facing the UK water industry today (Wilby, 2006).

2.2.4 Adaptation types

Two main approaches to adaptation have been identified. The first approach, bottom-up adaptation, is aimed at identifying and reducing community/system vulnerability and thereby reducing future exposure to potentially damaging impacts (Dessai et al., 2005). The second approach, top-down adaptation involves feeding downscaled climate information from general circulation models (GCM) into climate impact models and then using the output to inform adaptation.

A hybrid approach, combining elements of both top-down and bottom-up approaches has recently emerged (Brown and Wilby, 2012).

Scenario-led adaptation, the focus of this research, is dependent on the financial and technical capacity of the individuals undertaking the adaptation, their risk appetite and the type of adaptation options on offer (Adger et al., 2005; Dessai et al., 2005). As an approach it is also reliant on the individual having access to good quality, high resolution climate change information. Until recently, this has represented a significant barrier to adaptation; with increasing access to and availability of climate change information and more recently probabilistic climate change projections (e.g. UKCP09) we are now more than ever better placed to engage in scenario-led adaptation (Harris et al., 2012). Whether this additional climate change information is of any use and actually changes the way we make decisions however is an area of extensive debate within the scientific community and the focus of this research.

2.2.5 UKCIP & UKCP09

UKCIP was originally one of the principle agents of climate change adaptation in the UK; there is considerable evidence that UKCIP has injected vigour into climate change adaptation in the UK (Tompkins et al., 2010). However, the reliance on a single institution to reshape the socio-political landscape remains a challenge and only a small proportion of the UK's population has been exposed to some form of climate change adaptation since steps were taken to mainstream the concept (Tompkins et al., 2010).

Encouraging the undertaking of climate change impact assessments is one way of mainstreaming the concept of climate change adaptation. Climate change impact assessments are however beset by uncertainty; stemming from the choice and use of GCMs, future emission of GHG, their conversion into atmospheric concentrations and radiative forcing (New and Hulme, 2000; Jenkins and Lowe, 2003; Webster et al., 2003). The primary source of future climate change projections are GCMs. They are considered to be a vital tool for undertaking climate change impact assessments, which are capable of simulating complex earth systems including the atmosphere, oceans, land surface and sea-ice as

well as providing useful tools to study the impact of climate variability (Fowler et al., 2007).

In the UK, the current legitimate and credible suite of national suite of climate change projections is UKCP09, the product of a perturbed physics ensemble experiment of the HADCM3 and other global climate models (Murphy et al., 2009).

2.2.6 Probabilistic climate change projections

Probabilistic projections represent climate change as a probability distribution of potential outcomes, whereas deterministic projections represent climate change as a single definitive value. The previous iteration of the UK climate change projections UKCIP02, presented projections as the latter. In its present format, UKCP09 distinguishes between several different sources of uncertainty; including natural variability, climate models and GHG emissions. In developing the UKCP09 probabilistic projections, which systematically sample these uncertainties, it was necessary to develop new scientific methods using a series of purpose built sets of ensemble simulations using configurations of the HADCM3 and other climate models. UKCP09 used advanced statistical methods to generate probabilistic projections of future climate change and thereby explore the wider uncertainties in climate system processes. Some 10,000 probabilistic monthly change factors, hereby termed the UKCP09 10,000 sample ensemble, are available for three different GHG emission scenarios (low, medium and high) for seven 30 year time-slices (2020s, 2030s, 2040s, 2050s, 2060s, 2070s and 2080s). Future climate change is thus expressed as a large range of potential outcomes as opposed to a single 'most likely' projection (Dessai et al., 2009). The UKCP09 probabilistic projections were created using a Bayesian statistical framework to support interpretation of future systems from complex but uncertain models (Goldstein and Rougier, 2004; Rougier, 2007). The projections were designed to quantify the relative risk of different future outcomes, based on the physical understanding, observation evidence and the climate modelling technology currently available. As a result, they do not consider the full range of uncertainty, nor is this necessarily possible given the complex and uncertain

nature of the climate system (Murphy et al., 2009). In addition to the 10,000 sample ensemble, UKCP09 also provides an integrated weather generator (termed the UKCP09 weather generator) and 11SCP generated using 11 regional climate models (11RCM) with the aim of incorporating some of the uncertainty considered by UKCP09.

It can be argued that the move from deterministic UKCIP02, to probabilistic methods like UKCP09 of communicating climate change information has complicated the process of scenario-led adaptation considerably, given that it highlights uncertainty within the projections that was previously not communicated to decision makers who themselves maybe unfamiliar with it. It has been suggested that individuals faced with multiple equi-likely scenarios tend to adopt the middle or average scenario, often resulting in overconfident and inaccurate decisions with obvious economic and environmental implications. Basing decisions on the 'middle of the road' projection, when multiple probabilistic climate change projections are available can result in maladaptation and represents only a "small step forward" from using a single climate change projection such as UKCIP02 (Harris et al., 2012).

A comprehensive discussion of the different suite of projections provided by UKPC09, their merits and limitations and different ways of using and interpreting the projections is provided in CHAPTER 5.

2.2.7 Downscaling techniques

The raw probabilistic projections provided by UKCP09 are only available as monthly values, which on their own are insufficient for modelling most hydrological processes. Within UKCP09, two main approaches to downscaling are typically used to convert these projections into useful climate change information of an adequate spatial and temporal resolution.

The first approach is commonly referred to as "change factor" approach, elsewhere referred to as perturbation or the "delta-change" method (Prudhomme et al., 2002). A change factor is obtained for each month in the future series, these figures are then used to perturb an observed baseline daily series to

produce a future daily series i.e. applying a January monthly change factor of 10% to an observed series would make all of the daily values in the future series for the month of January +10% larger (Holman et al., 2009). This approach is however flawed, since it assumes that both the present and future are analogous in terms of climate variability and seasonality (e.g. they both assume the same number of rain days) (Diaz-Nieto and Wilby, 2005; Solomon, 2007). Due to limited data availability, projections are commonly based on a short observed record, resulting in future hydrological events generally being underestimated (Semenov and Barrow, 1997; Holman et al., 2009; Zhang et al., 2011). While the limitations of this particular approach have been known for some time, the relative simplicity and low computational demand of this approach means it is still in wide use (Diaz-Nieto and Wilby, 2005).

An alternate approach is to use a synthetic weather generator such as the UKCP09 weather generator, an example of a “science hidden” tool (Fowler et al., 2007; Harris et al., 2012) to communicate the projections at an appropriate temporal and spatial resolution that is sufficient for modelling future impacts as well as considering additional variability. The UKCP09 weather generator provides baseline and future daily and even hourly projections, at a spatial resolution of 5km (Jenkins, 2009). The UKCP09 weather generator is based around a stochastic rainfall model; other climate variables are then derived from a rainfall state using statistical relationships. Five rainfall states are considered; dry today/dry yesterday, dry today/wet yesterday, wet today/wet yesterday, wet today/dry yesterday and dry today/dry yesterday and the day before (Eames et al., 2012). It provides statistically credible synthetic climatology that is consistent with the underlying baseline and probabilistic future climate projections (Jones et al., 2009). Unlike the conventional change factor approach, weather generators are not dependant on the individual having access to a suitably long observed record (Green and Weatherhead, 2014b) nor do they assume that the future climate variability is necessarily stationary, making them an attractive candidate for supporting robust decision making (Groves and Lempert, 2007; Dessai et al., 2009; Lempert and Groves, 2010). Despite this, weather generators do however suffer from a number of known limitations including in the simulation of extreme

meteorological events. While they are theoretically the better choice, because they lend themselves to robust decision making, in reality they may not dramatically change the decision outcome (Green and Weatherhead, 2014b). They may even complicate the process of adaptation, being that they generally provide more information that can be realistically used by decision makers and have to be carefully calibrated using an observed dataset. A more detailed discussion of the merits, limitations and implications of different downscaling approaches is provided in CHAPTER 6. With the exception of CHAPTER 6, all subsequent workings are presented for the change factor method **only**, as this is one of the dominant downscaling approaches in the UK's environment sector.

2.2.8 Decision making

In the field of adaptation planning, decision makers often find themselves in situations of decision making under uncertainty, with incomplete knowledge about the states of nature that may occur and their probability. "Decision making under uncertainty" (French, 1986) has many names within the wider scientific literature including 'Knightian' uncertainty within the Info-gap literature (Ben-Haim, 2001; Ben-Haim, 2006) and deep uncertainty within the RAND literature (Lempert, 2003). In all cases it refers to situations of uncertainty where a probability distribution function cannot be assigned to the states of nature and is common in situations where information is scarce or subject to considerable uncertainty such as climate change (French, 1986).

Engineered solutions are often thought to be at the forefront of delivering adaptation (Dawson, 2007). These solutions are often expert driven, large scale and highly complex and as a result they also tend to be capital intensive (McEvoy et al, 2006; Morecroft and Cowan, 2010, Sovacool, 2011). Until now, many of these engineering solutions have just been extensions or upgrading of existing structures or practices e.g. flood levees, seawalls etc. (Blanco et al., 2009, Koetse and Rietveld, 2012; Ranger and Garbett-Shields, 2012), newer projects are however beginning to integrate climate change within the initial design (Wu et al, 2008). Limitations of engineered adaptation solutions generally fall into one of two categories, namely (1) being able to cope with uncertainties linked to future

weather, population growth and human behaviour (Dawson, 2007; Furlow et al., 2011) and (2) being able to justify their feasibility at the onset given the longevity and cost of engineers infrastructure (Koetse and Rietveld, 2012).

In the field of irrigated agriculture, decision makers have typically relied on the design dry year rule for estimating the volume of irrigation required. A design dry year is defined in the UK as a year with an 80% probability of non-exceedance, roughly equivalent to the older 'fourth driest year of five' rule of thumb. This rule of thumb is generally considered the 'best practice approach' and forms the basis of most water allocation decisions for UK irrigated agriculture (Weatherhead and Knox 2000). However, recent studies suggest that overreliance on the design dry year for asset design may risk maladaptation (Green and Weatherhead, 2014d). For SUDS, national design standards are beginning to emerge, with numerous storage estimation tools already in development (see Kellagher, 2011 for example).

Cost benefit analysis is commonly used to support decision making of these and other capital intensive engineer solutions, unfortunately this type of analysis and associated methodologies often require probabilities for each climate scenario. In situations of uncertainty it is not always possible to define (or even agree upon) probabilities for different climate scenario (IPCC, 2014b), in some situations it may entirely impossible to even identify a range of possible events (Gilboa 2010; Henry and Henry, 2002; Millner et al., 2010; Kunreuther et al., 2013), something that is especially true for events with low probabilities and high impacts or which have poorly understood risks (Weitzman, 2009; Kunreuther et al., 2013). In these situations, non-probabilistic decision criteria may be sought which dispense with probability of likelihood values all together to help decision makers decide what action to take (Ranger et al., 2010). These decision criteria are commonly used to support decision making under uncertainty i.e. in situations where no information of event likelihood exists (Dessai et al., 2009; Ranger et al., 2010). Several well-known decision criteria include Laplace's criterion (Laplace and Simon, 1951), Wald's Maximin criterion (Wald, 1945), Maximax criterion, Hurwicz's realism criterion (Hurwicz, 1951), and Savage's Minimax regret

criterion (Savage, 1951) and it is these that are the focus of this research. Laplace criterion originated in the 18th century and is based on the premise of symmetry (Ranger et al., 2010); each potential environmental state i.e. each climate change projection is considered to be equi-probable in the absence of prior knowledge. The average expected payoff for each option i.e. reservoir capacity is calculated using all the states i.e. climate projections; for Laplace, the option providing the largest average payoff is considered the design capacity. Maximin identifies the best option as the option which provides the largest expected outcome from the worst possible state. In contrast, Maximax identifies the best option as the option providing the largest outcome from the best possible state. The best option under Hurwicz's criterion is calculated using a weighted average of Maximin and Maximax with the weighting defined by α , representing the optimism of the decision maker. Minimax regret identifies the option with the smallest regret, representing the difference between the best and worst possible outcomes across all states. Alternatively, decision makers may seek to pursue options which exhibit "robustness", which perform well across a range of possible climate, socio-economic and other scenarios (Lempert and Schlesinger, 2000; Lempert et al., 2006; Lempert and Collins, 2007; Dessai and Hulme, 2007; Groves et al., 2008; Wilby and Dessai, 2010; WUCA, 2010; Brown et al., 2011; Lempert and Kalra, 2011). A large number of scenarios are commonly used to assess the vulnerability of options against uncertainties. Subtle or even big changes in options can then be identified to minimise potential vulnerabilities and ensure robustness. These type of approaches include decision methods such as Info-gap, which has previously been used to support decision making in water management (Ben-Haim, 2001; Ben-Haim, 2006; Korteling, et al., 2013), robust decision making (RDM) which has previously used in flood risk management and water management (Lempert and Groves, 2010; Lempert and Kalra, 2011; Matrosov et al., 2013) and robust control optimization (Hansen and Sargent, 2008). These decision methods are beyond the scope of this thesis which instead focuses on the non-probabilistic decision criteria introduced earlier. For a detailed explanation covering the methods used to generate all of the criteria and methods

discussed here readers are directed to Sniedovich, (2007) and Ranger et al., (2010) or more recently Green and Weatherhead, (2014c).

A comprehensive discussion of the merits, limitations and implications of different decision criterion is provided in CHAPTER 7.

2.2.9 Scenarios

Despite the relative abundance of decision criteria for situations of uncertainty, of which climate change adaptation is an example, real-world adaptation has until fairly recently witnessed limited uptake. This may be partly attributed to original scenarios underpinning the climate change projections. A scenario can be thought of as an image or story which describes what a potential future might look like. It should be reminded that scenarios are not predictions, but they are merely a description of the future environment, which may or may not be correct (Jäger et al., 2008). Scenarios are the primary tool for exploring the impacts of future climate change, and it is these which are sometimes considered to be incompatible with decision making under risk on account that they lack probability. The scenarios used here are the SRES B1, A1B, A1F1 scenarios, also commonly referred to as the low medium and high emission scenario within UKCP09 (Nakicenovic and Swart, 2000). They represent different 'story lines', interweaving complex social, economic and environmental factors (Polasky et al., 2011). All three scenarios, rather controversially, are regarded as equi-probable (Harris et al., 2012). It has been argued that the vast uncertainties surrounding future climate change, more so in the distant future make the prescription of probabilities unrealistic and an arguably subjective affair. Others have argued that the choice to not assign probabilities to either the original scenarios or the probabilistic projections provided by UKCP09 make the projections of limited value for decision making (Schneider, 2001; Schneider, 2006). Despite this, scenarios can contribute to learning and discussion as well as facilitate knowledge exchange. For example local scale visualisation of impacts and adaptation on realistic landscapes has recently emerged as a viable technology which can support dialogue on adaptation at the local scale (Schroth et al., 2011; Sheppard, 2012). Many studies exist which use climate, socio-economic and

other types of scenarios as the basis for assessing the impacts of future climate change, unfortunately the same cannot be said for studies which use scenarios as participatory tools to facilitate decision making on adaptation (Harrison et al, 2013).

2.2.10 Knowledge gap

There is now overwhelming evidence that recent climate change is attributable to anthropogenic activity (IPCC, 2013). Climate change can have potentially serious consequences for water resources (Leavesley, 1994; Wilby et al., 1994; Pilling and Jones, 1999; Arnell, 2003; Arnell, 2004) the ecology of freshwater ecosystems (Beaugrand and Reid, 2003; Moss et al., 2003; Hiscock et al., 2004; Sommer et al., 2004; Environment Agency, 2005) and their physiochemistry (Wilby et al., 1997; Hejzlar et al., 2003; Webb et al., 2003). However the extent and severity of climate change and its impacts on future water resources is difficult, even impossible, to quantify with any considerable accuracy. Despite this, climate change remains a significant challenge for the UK water industry as a result of legislative, ethical and environmental forces that will place increasing pressures on organisations to deliver and maintain services whilst protecting freshwater ecosystems from degradation (Arnell, 2011). It is vital that climate change and more importantly an awareness of its uncertainty are at the forefront of decision maker's minds as it can have significant consequences for water resources (Prudhomme and Davies, 2009).

Environmental management is plagued with uncertainty, despite this, little attention has until recently been given to the sensitivity of management decisions to uncertain environmental projections (Dessai and Hulme, 2007). Assuming that the future climate is stationary is no longer considered valid (Milly et al., 2008), nor is using a single or small number of potentially inaccurate projections to inform decisions. Instead, it is recommended that decision makers make use of increasingly available probabilistic projections of future climate change, such as those from perturbed physics ensembles like UKCP09, to gauge the severity and extent of ultimately uncertain impacts.

Probabilistic projections provide an attractive tool as they allow for partial quantification of uncertainty and ensuring they are used in a responsible manner can inform robust adaptation (Harris et al., 2012). These types of projections can be considered accurate as opposed to precise, they highlight a range of possible futures, only one of which, may or may not be the future reality (Dessai et al., 2009). Opinion is currently divided on how best to use and interpret probabilistic climate change projections (Stainforth et al., 2007). Some argue that “accurate, high resolution predictions of future climate are a prerequisite for developing effective responses to climate change impacts at regional scale” (Weaver et al., 2013, p. 40). This camp of thought is echoed in a number of papers including but not limited to (Collins, 2007; Barron, 2009; Doherty et al., 2009; Goddard et al., 2009; Shukla et al., 2009; Piao et al., 2010; Shapiro et al., 2010). Despite repeated calls for improvements, it is increasingly accepted that limitations in scientific understanding and computing power means it is not currently possible to model parts of the climate system that are “impact relevant” with any degree of accuracy, such as clouds, precipitation, winds, the diurnal cycle and atmospheric moisture balance (Randall et al., 2003; Randall and Fichet, 2007; Stephens et al., 2010; Liepert and Previdi, 2012).

It has been previously suggested that there is currently a “severe underutilisation” of climate models to support decision making, this has been widely reported and is believed to stem from the widespread and limiting belief that climate models which are capable of supporting planning must also provide higher resolution climate predictions. This combined with the apparent failure to integrate learning from the decision and social sciences into climate related decision support in particular sectors including water, agriculture and public health has exasperated problems. In order to alleviate these problems, it has been suggested that we need to aim to expand the concept of climate models, no longer treating them as prediction machines as part of a predict-then-act framework, but rather as exploration tools to assist critical thinking and scenario generation (Weaver et al., 2013). It is the area of research that this thesis has sought to explore in the context of local water management in the UK.

In doing so, it was necessary to evaluate current approaches for using probabilistic projections to support decision making for climate change adaptation planning, with a focus on local water management. A wealth of decision tools and methods have been developed to address problems of decision making under uncertainty and risk, too numerous to be compared here in any great detail and beyond the scope of this research project. Instead, the decision criteria which underpin many of these decision methods and that have been advocated for supporting climate change adaptation see Polasky et al., (2011) and Ranger et al., (2010) for example, have as far as the author is aware, never been critically compared using the UK probabilistic projections, one of the leading sources of “legitimate and credible” suites of national climate change projections in the UK (Tang and Dessai, 2012). Equally, studies comparing the different suite of tools provided by UKCP09, including the 11SCP and probabilistic projections and different methods of downscaling probabilistic projections while they do exist, such as Cloke et al., (2010); Kay and Jones, (2012); Christerson et al., (2012) and Daccache et al., (2012), none have explored the issues surrounding irrigation reservoir design or SUDS design, representing two contrasting approaches to local water management.

It is important to remember that climate change projections such as the UKCP09 probabilistic projections are only one part of a suite of tools and a broader system of decision making (Dessai et al., 2009). As a result of this, it is important to acknowledge the fact that information can be scientifically relevant without being decision-relevant, as is the case with the perceived saliency gap of UKCP09. Part of this maybe the lack of appropriate tools and techniques for dealing with probabilistic projections, whose probabilities, Bayesian, tend to differ to those probabilities, frequentist, used by traditional decision methods, discussed in more detail in subsequent chapters. As a result of this, uptake of probabilistic projections has been complicated and may have stalled process of adaptation.

Scientific information, like climate change projections can be useful for influencing decision making and supporting adaptation. However, in order to do so the information must be first deemed “credible, legitimate and salient”.

UKCP09 was reasonably successful because it fulfilled the first two requirements; however it has been demonstrated from small surveys involving multiple actors, that it is not necessarily salient (Tang and Dessai, 2012). As opposed to using the full technical capabilities of UKCP09, that from the perspective of knowledge producers is very impressive, decision makers have opted to go with the summary reports which accompany UKCP09 because they were deemed “less complex” (Tang and Dessai, 2012). This is because UKCP09, in its current format, does not necessarily provide all the required variables needed for informing adaptation such as information related to snow storms, lightning storms, heat waves and droughts. There is clear saliency gap in the knowledge that UKCP09 can provide and what is needed for supporting decision making (Arnell, 2011; Mylona, 2012).

The probabilistic projections provide a rich and complex dataset and integrating them successfully with decision making is a complex process. Much of the saliency gap associated with UKCP09 such as missing climate variables may be reduced over time and will vary on a case by case basis as knowledge improves. It is highly unlikely that the scientific community will return to the deterministic models of the past, probabilistic projections are very much here to stay despite arriving somewhat prematurely when compared against the development of decision support tools. A point exemplified by recent questions such as whether it is ethical to use a single probability distribution function to describe the likelihood of future climate change? (Lempert et al., 2013). They concluded that such as practice was unethical because it inhibits deliberation among individuals holding differing views, expectations and values. Furthermore, using a single probability distribution function can promote overconfidence in individual decision makers (Lempert et al., 2013), and if it is later proved to be incorrect or not representative of reality can result in maladaptation. Having access to multiple sets of plausible alternative probabilities is far better because it enables the analysis of multiple points of view whilst supporting systematic due diligence (Lempert et al., 2013).

The acknowledgement that probabilistic projections are difficult to integrate with decision making, despite being one of the preferred methods of communicating climate change uncertainty (Street et al., 2009; Tang and Dessai, 2012) leads on to the second part of the intended aim of the research which was to develop recommendations and improved methods for using probabilistic projections. The purpose of this method was to bridge the gap between the science of UKCP09 and its user base. Meaning it will be necessary to develop a new method that is accommodating of different decision makers risk attitudes, as different stakeholders perceive the usefulness of scientific information differently (Lemos and Rood, 2010) and the divergent nature of their values and perspectives (Cash et al., 2003; Cash et al., 2006). This method should be suitable for decision problems of deep uncertainty owing to the realisation that epistemic uncertainties in model structures, boundary conditions, human behaviour and future uncertainties including political, economic and social change cannot, at least at present, be fully quantified in a probabilistic way (Murphy et al., 2011). As a result of the additive and cascading nature of uncertainties it is very unlikely that uncertainties will be reduced sufficiently to determine likelihoods of climate change impacts needed to inform adaptation (Murphy et al., 2011). This point has been reaffirmed by Dessai et al., (2009) who identified that the uncertainty ranges for sensitivity analysis have not been reduced following 20 years at the top of the research agenda. It is highly likely that further investigation of epistemic uncertainties may in fact increase uncertainties by uncovering additional information about processes and feedbacks that were formally thought to be understood, such as the identification of processes linked with melting of large ice sheets on land (Murphy et al., 2011). It is the view of (Murphy et al., 2011) that “future decisions on climate change at the catchment scale will require the development of methodologies for decision making under conditions of deep uncertainty” and it is this call that we have sought to address through the undertaken of this research (Murphy et al., 2011, p. 84).

CHAPTER 3. ADAPTATION SCENARIO LED (TOP-DOWN) AND VULNERABILITY-LED (BOTTOM-UP)

3.1 Overview

The chapter begins by identifying and discussing the barriers and motivation for adaptation planning. The merits and limitations of scenario-led (top down), vulnerability led (bottom-up) and hybrids thereof are subsequently introduced and discussed.

3.2 Background

3.2.1 Introduction

Until recently, greater attention has been given to investigating the impacts of climate change than to climate change adaptation. Despite this, in recent years interest has grown in climate change adaptation due to the increased understanding that the past release of GHGs and climate change inertia will mean future adaptation is needed and will likely need to be anticipatory in its implementation (Bormann et al., 2012), irrespective of the success or failure of mitigation efforts. Climate change impact assessments addressing water resources are abundant in the literature, unfortunately the same cannot be said for the scientific output on water resource adaptation which consider what level of action is feasible, its geographic context and effectiveness. Adaptation in water resources is very important because of the scale and magnitude of potential climate change impacts and the consequences for humans, issues that may well be exasperated by existing non-climatic factors such as population and land-use changes (Smit and Pilifosova, 2003; Arnell, 2010). Climate change adaptation is now “the need of the hour” (Bhave et al., 2013, p. 1), particularly within the water sector given the complex and often interwoven nature of water resources.

Climate change adaptation planning is founded on the belief that a population or system can avoid potentially damaging climate change impacts through anticipatory or proactive action such as building new infrastructure or changing behaviour. Adaptation may involve building adaptive capacity, which in turn increases the ability of individuals, organisations and groups to adapt to changes

as well as implementing adaptation decisions which turns this capacity into action (Adger et al., 2007). Adaptation can be implemented well in advance of climate change or in response to experienced impacts associated with climate change. There are many types of adaptation, details of which can be found in Smit et al., (2000), these types are typically grouped on the basis of the institutional form they take, their purpose and mode of implementation (Adger et al., 2007). However it is often very difficult to identify when adaptation occurs as a direct result of climate change, since adaptation is not isolated from other decisions and as such is not immune to demographic, economic, cultural, information technologies and global governance changes, social conventions and globalising flows of capital as well as labour (O'Brien and Leichenko, 2000). For example an individual choosing to move from an area at increasing risk of flooding to an area at low risk may be principally motivated out of demographic or economic factors and not directly due to climate change.

3.2.2 Adaptation types

Two main approaches to adaptation; top down and bottom up, have been developed to attempt to characterise different methods of assessing climate change impacts and informing adaptation (Burton et al., 2005; Fussel, 2007). Top down adaptation, elsewhere referred to as scenario-led adaptation, typically involves undertaking a quantitative assessment of climate change, which is then combined with impact models to assess future impacts. Various adaptation measures can then be simultaneously compared by assessing their future performance against future impact models. Bottom up approaches, elsewhere referred to as vulnerability-led adaptation, typically use qualitative or even quantitative methods to characterise social vulnerability, adaptation measures can then be evaluated using participatory processes (Bhave et al., 2013).

3.2.3 Top-down adaptation

Until recently, the dominant approach to undertaking climate change impact assessments was to use projections from GCM to inform and quantify potential impacts (Wilby and Dessai, 2010). Top-down approaches typically begin by temporally and spatially downscaling climate change projections from GCMs and

a range of emission scenarios to produce local/regional scale projections. These projections can then be fed into impact models to estimate for example irrigation requirements, agriculture yield, runoff or river flows (Wilby and Dessai, 2010). Adaptation measures can then be evaluated to maximise any expected benefits or minimise any potential risks. Many examples of top-down approaches can be found in the literature. For example Rajagopalan et al., (2009) used stochastic simulations of climate change impacts, consistent with several GCM, to model impacts on stream flow and by extension the Colorado River. Lopez et al., (2009) assessed the implications on climate change on a water resource system using Phase 3 of the Coupled Model Intercomparison Project (CMIP3) and from a perturbed physics ensemble based on a single GCM. Vicuna et al., (2010) used sampling stochastic dynamic programming with a large number of GCM runs to model reservoir operations and adaptation. Vano et al., (2010) conducted a climate change impact assessment on an urban water supply system using twenty GCM climate change projections to model changes in hydrological regimes and reservoir storage and reliability in the Puget Sound Region. Similar examples of top-down adaptation can be found in Christensen and Lettenmaier, (2007), Brekke et al., (2009), Manning et al., (2009).

The term top-down adaptation is commonly used as information is cascaded down, beginning with the choice of emission scenario, GCMs, downscaling, impact model etc. Top-down adaptation approaches are useful for evaluating adaptation measures and characterising uncertainty issues when multiple climate change projections exist, however unlike bottom-up approaches they tend to ignore the “human factor”. In the case of top-down approaches, uncertainties are described and incorporated into the decision making process commonly using projections derived from multiple GCMs. In order to capture the full range of uncertainty, extreme members of a GCM ensemble are often used to model impacts, although it must be acknowledged that the full range of climate uncertainty remains unknown (Stainforth et al., 2007). Provided the range of scenarios is small and the number and range of outcomes minor then it is relatively easy to distinguish between desirable and less desirable options. However, if the scenarios are numerous and the number and range outcomes

significantly large, for example if one scenario points to inaction and the another suggests that very costly investment is needed, then the process of adaptation can be complicated (Brekke et al., 2008; Brekke et al., 2009). When addressing the worst possible outcomes, a decision maker is likely to only have limited access to a small number of projections. In these situations, decision makers are likely to be hesitant about committing the wealth of their resources, given the scale of investment that would be needed and the small number of projections on which options are typically based. Top-down adaptation is believed to make up the bulk of scientific evidence reviewed by the IPCC, however despite receiving support from the scientific community, until very recently few documented cases of adaptation resulting from this approach have occurred in reality (Wilby and Dessai, 2010). One reason for this is the “envelope” of uncertainty that tends to expand at each stage, starting with the choice of emission scenario through to the level of adaptation considered. As a result of the cascade of uncertainties, the practicality of most adaptation measures can be completely nullified. In time uncertainties may be reduced but they may also grow as we expand our knowledge of processes that we thought we understood, progress that will be largely dictated by the progress of the scientific community (Hawkins and Sutton, 2009). A significant barrier to top-down adaptation on a national scale is the considerable effort and time that must be invested in training user communities to establish the most appropriate tools and methods to use to inform adaptation (Wilby and Dessai, 2010). This was best exemplified by the release of UKCP09, which despite providing individuals with a wealth of tools for undertaking top-down adaptation, has not resulted in the desired mainstreaming of adaptation.

3.2.4 Bottom-up adaptation

As a result of the apparent failure of mitigation efforts and the threat of climate change to social vulnerability, interest in climate change adaptation has grown steadily in recent years. As a result of this a number of methodological and theoretical approaches have been developed to attempt to understand and assess vulnerability of society to climate, with the aim of developing adaptation strategies (Füssel and Klein, 2006; Berkhout, 2012; Fresque-Baxter and

Armitage, 2012). Bottom-up adaptation approaches aim to reduce vulnerability to past and present climate variability and tend to occur in response to an extreme event or a disaster as was witnessed in the wake of 1953 and 2000 floods in the UK and it is likely that it will become more popular again in response to the recent 2013/2014 floods. The term bottom-up adaptation is used because the evaluation of adaptation measures is founded on those factors and variables that influence successful adaptation at the individual, household and community level. However, unlike top-down adaptation, bottom-up adaptation does not require climate change scenarios or sufficiently lengthy observations in order to assess the frequency and magnitude of extreme events and their implications for society and the natural environment. In situations where observations are limited, formal records can be extended by the use of anecdotal evidence of impact (Wilby and Dessai, 2010). However while useful, there is a danger that extreme events in the local media can be over or under-reported. Bottom-up approaches provide legitimacy through stakeholder involvement, however unlike top-down approach they tend to give insufficient attention to physical factors and uncertainties (Dessai and Hulme, 2004; Bormann et al., 2012). Climate vulnerability is typically determined by a myriad of factors such as health, wealth, education status, social equity, food, physical and institutional infrastructure as well as technology (Brooks et al., 2005; Wilby and Dessai, 2010). Vulnerability indicators can be used to monitor changes in climate risk exposure and evaluate the success of adaptation strategies over time. Adaptation may involve improving coping facilitates such as upgrading flood warning systems or flood proofing (Wilby and Dessai, 2010), or in the case of Bangladesh building of earth platforms to protect against flood waters (Tanner et al., 2007). Alternatively adaptation may involve reducing exposure such as reducing the size of populations living in low-lying coastal areas or flood prone areas, such actions may involve encouraging pro-poor economic migration (Wilby and Dessai, 2010). A limitation of conventional vulnerability assessments is that they are generally less suitable for informing adaptation, especially in situations where climate change impacts occur which are beyond the range of recent experiences. Successive events, such as repeated droughts in rural-poor India, can progressively weaken coping

capacities, by increasing indebtedness of deteriorating health as a result food shortages. In these situations subsequent droughts will have a far greater impact compared with earlier events, as the local community is now in a much weaker state (Wilby and Dessai, 2010).

3.2.5 Hybrid adaptation

In order to inform holistic, relevant and implementable adaptation options, integration of top-down and bottom-up approaches and appropriate sequencing of activities is essential (Burton et al., 2005). Such “hybrid” approaches have previously been advocated by Wilby and Dessai, (2010), who outline a framework for identifying adaptation measures that are low regret, flexible, acknowledge other actions being taken or incorporate safety margins (Hallegatte, 2009; Wilby and Dessai, 2010). Given the already large uncertainties in the future climate and with vulnerabilities of some populations, it is far from surprising that should we prioritise robust adaptation strategies which perform adequately over a range of outcomes as opposed to optimum strategies which perform excellent for a small number of outcomes. In an ideal world, no regret solutions should be beneficial regardless of whether climate change actually occurs, however this is seldom a reality and the term “low regret” is typically more appropriate given the opportunity costs, trade-offs and externalities that typically result from adaptation (Wilby and Dessai, 2010).

Hybrid approaches, as described by Wilby and Dessai, (2010) typically begin by identifying the most significant climatic and non-climatic risks associated with future climate change, next a large selection of potential adaptation strategies can be identified, which can include both soft and hard engineering solutions. From this large list of potential strategies, a sub-set of adaptation strategies can be identified which would reduce vulnerability of the existing population or system on the basis of the current climate regime whilst remaining socially acceptable, economically sustainable and technically feasible, in line with most bottom-up approaches to adaptation. Regional downscaled climate change projections can then be used as part of a more detailed option appraisal to characterise upper and lower bounds for climate change sensitivity analysis, similarly to how most

top-down approaches would proceed. Even in situations where no downscaled projections are available, narratives from GCMs or qualitative descriptors of the direction and variability of future climate change can even be used to identify options which are more resilient to uncertainty (Wilby and Dessai, 2010). Measures that perform satisfactory when exposed to these uncertainties or meet accepted principles can then be considered robust and should be favoured over other less robust strategies (Wilby and Dessai, 2010).

Given the wealth of approaches available to decision makers seeking to engage in adaptation, it is not unsurprising that opinion is divided with regards to the best method to use for informing adaptation. Some individuals are calling for more sophisticated GCMs which are capable of providing higher resolution projections that better characterise and constrain uncertainty so that decision makers can make informed decisions. Others argue that addressing current climate variability and the issues it creates, particularly for vulnerable communities are enough for now (Washington et al., 2006). It is the view of Wilby and Dessai, (2010) that significant benefits will arise just by allowing climate change option appraisal to “take centre stage” and for now let climate change scenarios take a back seat. Steps can be taken today, even in situations of limited data, to mainstream adaptation. Even decadal projections of the future climate can provide boundaries for sensitivity analysis; however in order for this to be successful we need to shift our focus from identifying optimal strategies to robust strategies (Lempert et al., 2004). For this to happen we need to encourage more data sharing so that the most vulnerable regions across the globe are not placed at undue risk of catastrophic impacts associated with future climate change (Wilby and Dessai, 2010).

3.2.6 Motivation

Climate change is already adversely affecting biodiversity, genetic resources and ecological systems and the services derived from them (Convention on Biological Diversity, 2009; Mooney et al., 2009; Hoegh-Guldberg, 2011). The preservation of natural systems is essential for human prosperity, food security, welfare, health and livelihoods (IPCC, 2014b). Numerous benefits can be derived from their

preservation, for example coral reefs and coastal wetlands can help protect against storm surges and provides opportunities for recreation (Hoegh-Guldberg, 2011), fisheries and aquaculture provide 20% of the dietary protein of 1.5 billion people (IPCC, 2014) and wetlands and green spaces can help to control runoff associated with increasing precipitation (Jentsch and Beierkuhnlein, 2008; Mooney et al., 2009). Across the globe, societies, organisation and individuals have adjusted their behaviour in response to experienced climatic events, others are currently contemplating whether to adapt to future climate change, some are taking active to steps to mainstream adaptation and a small proportion maintain that climate change isn't actually occurring or isn't related to continued human activities (Adger et al., 2005; McCright and Dunlap, 2011). Much of the adaptation that has taken place to date has been reactive, that is it occurred in response to past or current climatic events (Adger et al., 2005). Many factors can motivate adaptation including, but not limited to the protection of economic wellbeing or improvements in safety (Adger et al., 2005). There are many routes to adaptation, some of which have been discussed by Smit et al., (2000) and Wilby and Dessai, (2010). It is often difficult to separate adaptation decisions resulting from climate change and adaptation triggered by other factors including social, economic drivers, issues or unrest. There is however examples of adaptation occurring as a direct result of climate change. However, these actions are typically the result of government led initiatives, as can be seen in the case of UKCIP in the UK, which was set up with the sole goal of supporting and encouraging climate change adaptation. Regardless, successful adaptation can result in a host of short term and long term benefits depending on the timing and scale of the adaptation, though they can also generate costs and create issues when uncertainties are large or where adaptation in one locality negatively impacts the resilience of another locality. Generally speaking, adaptation aims to reduce vulnerability or enhance resilience (Adger et al., 2007). However on a personal level, some studies suggest that adaptation of an individual who is exposed to or sensitive to climate change is motivated to a large extent by that individuals "belief in climate change" and a belief in an innate adaptive capacity. This view is

contrary to the belief that adaptation is driven solely by economic-socio-political factors (Blennow and Persson, 2009).

Others attribute climate change adaptation to the impacts of climate change, including experienced or perceived events such as changing weather patterns, legislation including sustainable development standards and EU common policies, flooding, conservation, risk management, cost savings and societal pressures related to change development and population (Tompkins et al., 2010). Real or perceived climate change has been cited as the primary driver of climate change adaptation as seen in the case of the Construction Industry Research and Information Association which have a project which aims to provide practical guidance for large construction projects dealing with climate change risks. This project is aimed at providing contractors with the necessary tools to diagnose and manage technical risks associated with future climate change (Tompkins et al., 2010). Legislation has been cited as another key driver of adaptation, although interestingly the legislation driving climate change adaptation is not necessary climate change legalisation. That is because government policies at the European level and national level are inadvertently encouraging action which produces adaptation as a by-product (Tompkins et al., 2010). Examples of these indirect drivers of climate change adaptation can be seen from Water industry in England and Wales, which under section 93A of the Water industry Act are encouraged to promote greater water efficiency among their customers (Tompkins et al., 2010). Floods are one of the more tangible drivers of climate change, as direct or indirect exposure to flooding can drive action. For example, in SEPA has begun to invest quite heavily in SUDS to improve road drainage, however by improving drainage and the coping capacity of sewers they have helped vulnerable areas which may become exposed to autumn floods to be less exposed (Tompkins et al., 2010).

3.2.7 Barriers

UKCP09 represents the product of seven years of work and a consortium of organisations including Department of Environment, Food and Rural Affairs (DEFRA), UKCIP and the Met Office (Tang and Dessai, 2012) at a combined cost

of £11 million or £0.18 per citizen (Kelly, 2014). UKCP09 was “purposefully designed to meet the needs of a wide range of people who will want to assess the potential impacts of the projected future climate and explore adaptation options to address those impacts” (UK Climate Impacts Programme, 2014). The scientific methods underpinning UKCP09 have however divided opinion, evident by the number of high profile objections to the science of UKCP09, which have emerged in the public domain in recent years including Ghosh, (2009) and more recently Bennett, (2013), the contents of which have not yet been substantiated.

The move from deterministic to probabilistic methods of communicating climate change information was perhaps the most controversial decision surrounding UKCP09. The move from one projection to an ensemble of projections per emission scenario has created difficulties for some users, evident from the adaptation reports of Transport Scotland and Hertfordshire County Council (Kelly, 2014). As if to further complicate matters, the probabilistic projections provided by UKCP09, are not without their controversy. The type of probability used by the probabilistic projections, Bayesian, is less familiar to decision makers, who are more familiar with and accustomed to using frequentist probabilities, whose probability is defined as the frequency of an event based on a large number of observations of the event in that particular state (Dessai and Hulme, 2004; Stainforth et al., 2007). “All the probabilistic estimates [UKCP09] did are all very difficult to interpret because they are not probabilities in the way that a decision-maker would use probabilities” (Tang and Dessai, 2012, p. 308). Bayesian probabilities are less favoured by decision makers because they are subjective and thus limit their practical application, making them less suitable for supporting robust decision making (Reeder and Ranger, 2011; Tang and Dessai, 2012). The arena that decision makers now find themselves in highlights an ongoing disconnect in the science-policy interface between what decision makers want and what scientists are actually producing, thereby complicating the process of adaptation (Shackley and Wynne, 1995; Knorr-Cetina, 1999). However, by carefully considering the difficulties and challenges facing decision makers we can attempt to bridge this gap by creating new techniques and tools (Harris et al., 2012)

Despite being less favoured by decision makers, many decision makers maintain that UKCP09 is “credible” and “legitimate”, some individuals going as far as to suggest that Bayesian probabilities enhance that credibility, because it makes people realise the inherent uncertainties, thereby leading to better planning (Tang and Dessai, 2012). It is the conclusions of Tang and Dessai, (2012) that “advances in scientific understanding, greater acknowledgement of uncertainty and greater user input have helped install credibility and legitimacy in UKCP09” (Tang and Dessai, 2012, p.310). However, these advances have however come at the expense of saliency, many decision makers feel UKCP09 is overly complex and highlighted difficulties using its raw outputs, instead opting to use the maps and figures designed for public consumption opposed to its full technical capabilities (Tang and Dessai, 2012).

The Bayesian probabilities underpinning UKCP09 are not the sole reason for the perceived saliency gap associated with UKCP09, the scientific ability and willingness of an individual to use information have both been cited as reasons (Tang and Dessai, 2012). Difficulties using information from UKCP09 has been compounded by the fact that the individual doing the modelling is not necessarily the same person as the one making the decision. Those individuals in senior management, whose job it is to decide what to do, do not always understand the science in sufficient detail or are less familiar with the concept of probabilistic climate change information (Tang and Dessai, 2012). Instead of several possible answers, which probabilistic climate change projection tend to highlight, decision makers often seek a single objective answer. While decision makers appreciate having a better understanding of the uncertainty, they are dissatisfied that UKCP09 has complicated decision making (Tang and Dessai, 2012). UKCP09 has gone some way in fulfilling calls for more transparency about uncertainty in climate change projections (Patt and Dessai, 2005). However the probabilistic terminology used by UKCP09 can be construed as misleading, because probabilistic projections are often based on relatively few models, which themselves are simplifications of reality. In the case of UKCP09, an ensemble of 280 HadSM3 experiments were run, sampling the effects of perturbing these parameters relative to the standard parameter values used in HADCM3 (Gordon

et al., 2000). As a result, it is necessary to accept that the true uncertainties are likely to have been underestimated. As a result of this and the saliency gap associated with UKCP09 concerning some of its climate variables, many individuals feel that the information provided by UKCP09 is difficult to integrate successfully into decision making and “moves the individual away from a decision” (Tang and Dessai, 2012, p. 308).

Adaptation decisions regularly need to be made in the face of overwhelming uncertainty, linked to various sources including demography, technology and economic futures. Climate change adds an additional layer uncertainty, linked to socio-economic development pathways, future climate policies, adaptation and reaction of ecosystems, all of which can have significant implications for the extent and patterns of future climate change (IPCC, 2014b). These and other uncertainties have previously been shown to a major barrier to successful adaptation in Mozambique (Patt and Schröter, 2008). Numerous other barriers to adaptation have also been identified, details of which can be found in Moser and Ekstrom, (2010), Gifford, (2011) and Measham et al., (2011) among others. For examples barriers to adaptation can emerge as a result of social and cultural factors which can be linked to world views, cultural norms and behaviours (O'Brien, 2009; Moser and Ekstrom, 2010; O'Brien and Wolf, 2010; Hartzell-Nichols, 2011). Social and cultural norms can affect people's perception of risk and determine which adaptation options are deemed appropriate as well as influence their adaptive capacity and the vulnerability of different elements of society (Grothmann and Patt, 2005; Weber, 2006; Patt and Schröter, 2008; Kuruppu, 2009; Adger et al., 2009; O'Brien, 2009; Nielsen and Reenberg, 2010; Wolf and Moser, 2011; Wolf et al., 2013). Access to fiscal capital has also been shown to be a significant barrier to adaptation, especially considering the significant global costs that adaptation is likely to incur over the coming decades, with recent estimates suggesting costs in the region of \$75-100 billion per year by 2050 (IPCC, 2014b). While capital has been made available to support adaptation, it is suspected that the demand for adaptation finance currently exceeds available resources (Bouwer and Aerts, 2006; Flåm and Skjærseth, 2009; Hof et al., 2009). Various other barriers have also been identified and

categorised, details of which can be found in IPCC (2014b). These are too numerous to be listed here in any great detail but can include barriers such as knowledge, awareness, technology, physical system, biological, economic, human resource, governance, institutional and barriers arising due to competing values (IPCC, 2014).

Barriers to adaptation may be characterised by which phase they appear within the decision making process. These phases may be defined as understanding the problem, planning adaptation actions and managing the implementation of option(s). Within each of these phases there are multiple stages, each of which may give rise to potential barriers (Moser and Ekstrom, 2010). Beginning with the understanding phase, barriers may arise as a result of difficulties or an inability due to different mental models to detect/accept the existence of a definitive climate signal or problem. Barriers may occur during the gathering/collection of data, arising due to lack of availability and accessibility to data, its saliency and credibility. They may also arise depending on the receptivity of the individual to the information and whether or not they are actually willing to use it. Barriers emerging during the planning phase typically occur as a result of a lack of leadership or difficulties agreeing goals and options. Similarly, credibility, legitimacy, availability and accessibility of information as well as methodologies to compare options may create additional barriers. Finally, barriers may occur during the management phase, and are associated with the implementation of options, monitoring outcomes and evaluating the effectiveness of options. Typically they are the result of resource constraints e.g. fiscal, technical etc., legality and procedural feasibility and willingness to learn and revisit previous decisions (Moser and Ekstrom, 2010).

Numerous psychological barriers to climate change action and adaptation also exist. For example cognitive dissonance can be demonstrated by individuals who behave in irrational ways if they have already invested in something that later is proved to be detrimental or a “sunk cost”. Individuals who have invested in fossil fuels provides some of the greatest examples of cognitive dissonance (Gifford et al., 2011). “It is often easier to escape in other ways – by ignoring or forgetting

the advice or by finding a way to escape that does not require solving a problem” (Skinner, 1987, p. 5). Environmental numbness can arise in situations in which a message is broadcast so regularly that attention to it actually decreases. This problem can be exasperated if the message is not varied, as in the case of the environment or climate change, leading to numbness in the audience and ultimately inaction (Gifford et al., 2011). Optimism bias has also been shown from the reactions of individuals on a global scale. Many believe that conditions will worsen over the next 25 years, however these conditions “will not be as bad” where they live but will occur elsewhere (Gifford et al., 2009). Denial that climate change is a reality is perhaps the most well-known and regularly cited reason for inaction, sunk costs, uncertainty and mistrust all gather together in the minds of some individuals (Gifford, 2011). Active denial of the problem at hand is a genuine concern, questions like whether climate change is occurring, is it caused by humans or can climate change be linked to behaviour and actions on an individual scale, continue to be asked (Norgaard, 2006). A much wider list of psychological barriers to climate change action and adaptation is presented elsewhere and in much greater detail, for example Gifford, (2011). Overcoming many of these barriers is beyond the scope of this thesis and in the opinion of this author the actions of any one individual. Many of these barriers are engrained in large swathes of the world’s population and will take many years and maybe even direct exposure to climate change impacts to be undone. As a result, the focus of this research should not be those individuals that refuse to adapt, but those individuals that are willing but don’t know how to adapt or don’t have access to the appropriate tools to enable them to adapt.

3.2.8 Discussion

It has been suggested that adaptation to climate change is not a homogenous process, it is influenced by a number of factors, not least the ones considered here but also class, gender and culture. Understanding the cultural barriers to adaptation warrants the undertaking of micro-scale and context-specific studies given the contextual nature of the problem (Tompkins and Neil Adger, 2005; Coulthard, 2008). It is acknowledged that different stakeholders will differ in their

perception, experience and evaluations of risk in addition to how they act to reduce or eliminate these risks. For example, farmers in the same geographic area may have very different perceptions of risk and when faced with uncertainty in the future climate change may react very differently. Some individuals may be quick to change their current behaviour, while others may react more slowly or even favour inaction given the vast uncertainties faced (Dow et al., 2013). Real or perceived uncertainty can reduce the frequency of pro-environmental behaviour, as demonstrated by a number of research studies addressing resource dilemmas (Hine and Gifford, 1996; de Kwaadsteniet, 2007). Climate change uncertainty is regularly cited as a justification of inaction. In the case of the IPCC, the choice of terminology such as “likely” and “very likely” in the Fourth Assessment Report (Solomon, 2007) meant many individuals interpreted the phrases as having a lower probability than intended by the IPCC experts (Budescu et al., 2009). On the part of the lay audience, the well-intended efforts of climate scientists to describe the degree of certainty have led many individuals to underestimate climate change risks (Gifford et al., 2011). Uncertainty is an “inescapable element of any climate model – or any model” as a result climate scientists increasingly find themselves in a difficult problem of how to best present information about the likelihood and extent of future climate change without providing information that might later prove to be incorrect (Gifford, 2011). Clearly, any approach tailored towards informing adaptation would need to consider and evaluate options which are the product of subtle and not so subtle differences in terms of the risk perception of the individual and willingness to adapt to climate change.

CHAPTER 4. MODELLING: IRRIGATION DEMAND AND URBAN RUNOFF

4.1 Overview

This chapter begins by introducing the two case studies, including an overview of the current methods used in each respective field. The geographic sites underpinning this thesis are described, providing reasons for their selection and details of their climatology. The methodology used to generate the future climatology, including details of the datasets used are provided. The daily soil water balance model, WaSim, used to inform the design of a series of irrigation reservoirs and SUDS at each of the investigated sites are described, providing reasons of selection and modelling capabilities. The methodology used to calculate the irrigation reservoir capacities needed to meet future water demands of a potato crop is outlined, along with an overview of the cost-benefit analysis methodology and assumptions used. The methodology used to calculate the capacity of various SUDS and traditional drainage devices are provided, along with an overview of the cost-benefit analysis methodology and assumptions used. A graphical diagram depicting the steps taken to identify decision outcomes is also provided for each case study. Finally a short summary is provided, detailing how the data from this chapter will be used, though much of this detail is provided in subsequent chapters.

4.2 Background

4.2.1 Introduction

Two contrasting case studies were selected to evaluate current approaches and develop recommendations and improved methods for using probabilistic projections to support decision making for climate change adaptation planning for local water management. These case studies consisted of an agriculture irrigation reservoir case study and an urban drainage SUDS case study. In both instances, a range of irrigation reservoirs and SUDS were compared on the basis of their performance when exposed to future climate change projections. These contrasting case studies were selected as there are few resources globally that

are more complex, engrained in everyday life and integral to our future survival than water. The first of these two case studies, irrigation reservoirs, outlines a decision problem where a water deficit or a lack of water is the dominant issue. SUDS on other hand represent a situation where a water excess or having too much water is the problem. Irrigated agriculture

A reliable water supply is integral to many industries particularly the irrigated agribusiness, and water stress has obvious implications for food production, rural businesses and rural employment (Knox et al., 2009; Daccache et al., 2011). Agriculture is one of the major land uses in the world and a major economic, social and cultural hub, providing a wealth of ecosystem services that may be placed at increased risk due to climate change. Approximately 1.2-1.5 billion hectares are currently used to worldwide grow crops, while about 3.5 billion hectares is used by grazing animals with another 4 billion hectares of forests presently being managed to differing degrees. In order to meet projected changes in human population and per capita food demand, production will need to continue to increase as it has done in the past and eventually even double in size (Howden et al., 2007)

Agriculture is one sector that is expected to experience both direct and indirect impacts attributed to climate change, the severity of which will depend on latitude and the vulnerability of the system in question among other factors (Kundzewicz and Robson, 2004; Abraha and Savage, 2006; Kang et al., 2009). Higher average temperatures in conjunction with a reduction in frost damage during winter is expected to provide longer growing periods, promote faster crop emergence and in turn support larger yields (Peiris et al., 1996; Döll, 2002; Popova and Kercheva, 2005). Climate change could potentially decrease the crop rotation period and encourage farmers to diversify what crops are planted, adopt mixed varieties, vary sowing dates, fertilisations dates and adjust crop levels (Cuculeanu et al., 2002). Conversely, warmer average temperatures could increase the prevalence of pests and diseases with more extreme events and greater weather variability potentially causing substantial crop damage. Effects may also be felt through indirect impacts including changing irrigation demand patterns (Holden et al.,

2003) and escalating water demand. Reduced summer rainfall may increase soil moisture deficits meaning more supplemental irrigation is needed (Kang et al., 2009). Alarming, climate change could even destabilise global markets for agricultural commodities with significant implications for UK agricultural producers and consumers. Agriculture is very sensitive to climate variability, which is one of the dominant sources of production variability and disruption to ecosystem services (Howden et al., 2007). As a result of this sensitivity and other considerations listed in Table 4.1, there is strong rationale for adapting to future climate change.

Table 4.1 Reasons for adapting to future climate change. Adapted from Howden et al., (2007).

Reasons for adapting to future climate change
Past GHG will contribute to approximately $\approx 0.1^{\circ}\text{C}$ of warming per decade for several decades, meaning some form of adaptation will be necessary to manage impacts.
GHG are continuing to increase, with subsequent changes in atmospheric CO_2 , sea level and global temperatures at the high end of the scenarios considered by the IPCC.
Emission-reduction efforts such as the Kyoto Protocol have been unsuccessful, resulting in increasing concerns about future emissions
The high end of the climate change scenario range has increased over time, higher potential temperatures may have nonlinear and increasingly negative impacts for agriculture.
Climate change may provide opportunities for investment in agriculture, rewarding early action taken against potential future changes.

Irrigated agriculture is a small but vital sector in England and Wales, employing approximately 50,000 people while contributing about £3 billion to local rural communities. Increasing demand, climate change and the need to balance environmental demands are already adversely affecting the availability of water for irrigation (Knox et al., 2010). In England alone, during a dry year approximately 150,000 hectares are irrigated providing the food market with substantial quantities of horticultural produce, most notably potatoes. The sustainability of irrigated production is however under threat from competition for water resources from other sectors and new legislation designed to enhance

environmental protection and climate change (Knox et al., 2010). Rising demand for public mains water supply combined with recent droughts and increased environmental protection has led to a reduction in the availability of water for agricultural and horticultural irrigation in England and Wales (Weatherhead et al., 2008).

Abstraction of water for irrigation in England and Wales is regulated by the Environment Agency (EA) which is responsible for granting abstraction licences which govern the volume and time that water can be abstracted (Freeman, 2005). Section 57 of the Water Resource Act 1991 titled “Emergency variation of licenses for spray irrigation purposes” stipulates that temporary restrictions may be placed on abstraction for spray irrigation (representing the dominant method of irrigation in the UK) in response to exceptional shortages of rain or other emergencies. Under section 57 of the Water Resource Act 1991, the EA can serve notices restricting the amount of abstraction if it is believed that the abstraction is likely to affect the flow, level or volume of any inland waters. Three broad categories of abstraction licences exist; summer abstraction licences which grant abstraction between 1st April and 31st October, winter abstraction licenses which grant abstraction between 1st November and 31st March and all-year abstraction licences. While the volume abstracted for irrigation in England is relatively small, it peaks during summer months when water resources are most strained, and can create conflict with other demands for water, most notably for the public water supply and environmental protection (Daccache et al., 2011). Summer water resources in many catchments are already fully licensed and some are over licensed or even over abstracted (Knox et al., 2010). Additional irrigation abstraction licenses are unlikely to be granted, despite increasing demand for water for irrigation (Knox et al., 2010). Many existing summer sources are becoming increasingly unreliable and new licenses for summer abstractions are now widely unobtainable or are issued with tight restrictions. There is pressure to reduce excessively large licenses. Where water is available, applicants for renewal of existing time-limited licences and/or additional abstractions are required to show a “reasonable need” for the water they request.

4.2.2 Irrigation demand management

In response to the pressures placed on water resources for irrigation, farmers may adopt new irrigation systems such as switching from traditional spray irrigation systems to more efficient drip fed irrigation systems (Defra, 2002). In addition farmers, agribusiness and water resource managers are also increasingly being encouraged to adopt irrigation reservoirs as part of their wider water resource strategy (Weatherhead et al., 2008). Many UK farmers have begun investing in reservoirs in drier parts of the country in order to secure water supplies for irrigating high value fruit and vegetables. Farmers with access to a water-filled reservoir can ensure the environmental impact of irrigation abstraction during summer months, when water resources are most constrained (Weatherhead et al., 2008). Many farmers take advantage of winter abstraction licences to fill their reservoirs, stream flows are higher and abstraction charges during winter are generally cheaper than equivalent summer abstraction charges because the resources available are typically more plentiful (Environment Agency, 2013).

In addition, farmers may reconsider when and how often to irrigate their crops, a problem commonly referred to as irrigation scheduling. The purpose of irrigation scheduling is to determine the optimum amount of water to apply to a field and timing of application to maintain crop yield and quality (Bailey, 1993). Efficient irrigation scheduling should consider plant type, atmospheric conditions, and soil characteristics and most typically aim to maintain soil water content close to field capacity (Anadranistakis et al., 2000; Jones, 2004). As a result of recent water shortages and mounting irrigation costs, new methods of irrigation continue to be developed. The introduction of precision irrigation methods such as trickle irrigation systems have dramatically reduced the amount of water needed for irrigation, however their advent has also highlighted the demand for new irrigation scheduling methods and controls. Regulated deficit irrigation (RDI) is based on the principle that maintaining a slight plant water deficit can control excessive vegetative growth and improve the partitioning of carbohydrates to reproductive structures such as fruit (Chalmers et al., 1981). An alternative method is partial root-zone drying (PRD), which works by alternating where irrigation is received

by the root system (Dry and Loveys, 1998; Stoll et al., 2000). While these methods are subject to their own advantages and disadvantages, the choice of scheduling method depends to a large extent on the objectives of the irrigator and the irrigation systems that are available. For example, RDI requires the water status to be maintained in a rather narrow tolerance as any excess application negates the advantage of maintaining a regulated deficit, whereas under application may result in losses in yield and/or quality (Jones, 2004). Generally speaking, more advanced scheduling systems require higher-precision application systems, thus for the purpose of the research the decision was taken to use a relatively simple rule based scheduling system in combination with a one-dimensional soil water balance model on that basis that (1) more advanced irrigation schedules typically warrant specialist irrigation systems which may or may not be available, (2) effective operation of such systems would require access to real time and/or frequent observations which would rule out manual monitoring programmes and would require automated monitoring systems which may or may not be available and (3) a more simplified irrigation schedule would not necessarily improve or detract from our ability to answer the research original question. Further details of the irrigation schedule and soil balance model used are discussed in section 4.3.3 of this chapter.

4.2.3 Potato irrigation

The average irrigation depth in the UK ranges between 40 - 60 mm for soft fruits and 150 - 220 mm for potatoes (Morris et al., 2004). In terms of the volume of water used for irrigation, the east of England has the largest demand, approximately 50%, followed by the Midlands, about 19%, the Thames region 10% and the South 9%. Based on a 2010 survey, irrigation was found to contribute approximately 38% of agricultural water use in England, equivalent to 184 million m³ of water used (Defra, 2011).

Potatoes (*Solanum tuberosum* L.) are the most important irrigated crop in the UK, accounting for 43% of the total irrigated area and 56% of the total volume of water abstracted in the UK (Knox et al., 2009). The dominant variety is Maris Piper, which accounts for 126,328 hectares of planted area followed by Estima which

accounts for 7,740 hectares of planted area. A previous study by Morris et al., (2004) found that about 50% of all potatoes grown in England and Wales are irrigated partly to ensure quality assurance. Insufficient irrigation can result in potatoes developing potato scab while over-irrigating can result in water, energy and labour expenditure with obvious economic implications (MacKerron, 1993; Hess et al., 2009). Their sparse root system, 85% of their root length is concentrated in the upper 0.3m soil layer, mean potatoes are particularly sensitive to moisture stress (Opena and Porter, 1999).

As of 2009, the UK was ranked sixth in the world for potato production, producing some 326 million metric tonnes of potatoes (Potato Council, 2011). As of 2011, most of which were planted in Eastern England 33,171 hectares followed by Scotland 29,355 ha, East Midlands 18,538 hectares and West Midlands 15,296 hectares (Morris et al., 2004). The UK potato industry has changed dramatically in recent decades, from a relatively small sector consisting of individual farm to a much larger consortium of major agri-business. Between 1960 and 2010 registered growers decreased by 96% from a total of 76,825 in 2060 to 2,465 in 2010, while total planted area has decreased by 57% from 280,200 hectares in 1960 to 120,300 hectares in 2010. Area per grown on the other hand has increased by a massive 1,237% from 3.65 hectares in 1960 to 48.8 hectares in 2010. Despite this total production has remained relatively stable at approximately 6.56 billion tonnes in 1960 and approximately 5.85 billion tonnes in 2010, a reduction of only 11% (Potato Council, 2011). This shift in production has been principally attributed to rising demand for high quality produce, most easily met by irrigation; this has in turn led to greater interest in irrigation demand modelling and the construction of irrigation reservoirs, the focus of this research, across the industry as a whole (Knox et al., 2010).

4.2.4 Urban drainage

Like agriculture, urban drainage and the sustainable management of urban environments is at risk of impacts associated with future climate change. "Climate change is the biggest threat to the future development of human civilisation and poses a huge challenge to cities like London" (Authority, 2007). The urban

environment, like agriculture may potentially experience both direct and indirect impacts associated with future climate change. Receiving watercourses can become highly polluted especially when large storm flows arise during intense precipitation events generates a 'flushing' effect on the drainage system (Gnecco et al., 2005; Mannina and Viviani, 2010). Climate change may produce more intense and prolonged precipitation events which will push flood defences to their limits, placing increased strain on our sewer systems resulting in more frequent surcharging/flooding (White and Howe, 2004). Flooding of cities can be particularly catastrophic as a result of the susceptibility of the infrastructure they typically contain. For example, in 2002 a 1 in 100 year event across Europe resulted in billions of euros of damage, dozens of deaths and many thousands of people made homeless most notably in Austria, Czech Republic, Germany and Poland (Charlesworth, 2010). In the UK, the devastation caused by the 2007 and 2008 floods highlighted that the current sewer infrastructure in the UK is inadequate, even if future conditions remain at the conservative end of current projections impacts are likely to intensify. The 2007 UK floods alone were responsible for 13 deaths, flooding of 48,000 homes and 7,300 business with a total cost of £4 billion including £1 billion of clean-up operations (Chatterton et al., 2010). A solution to the risks posed by flooding would be to increase the capacity of existing pipes, though as an approach this remains a relatively blunt solution and can be incredibly expensive, "bigger pipes are not the solution for bigger storms" (Water UK, 2008, p. 5). The water industry can invest in the sewer network to build extra resilience at a considerable cost, though sewers and drains are not flood defences. Situations may arise where the sewer network cannot cope with the volume of runoff produced during extreme events, while new designs standards which consider overland flow routes can be set, SUDS and sacrificial flood areas may provide an alternative solution to piped sewer systems for the disposal of surface water and thereby reduce the risk of pluvial flooding (Water UK, 2008).

Foul sewage output from homes and businesses is easy to predict and accommodate; storm flow is however much harder to predict and subsequently control due to the stochastic nature of precipitation (Butler and Davies, 2004; Jones and Macdonald, 2007). Urban impacts may occur in the form of increased

flooding and sediment deposition, sewer overflows, water quality impairment and aquatic habitat degradation (Paul and Meyer, 2001; Bibby and Webster-Brown, 2005; Roy et al., 2005; Walsh et al., 2005). In addition to dealing with current issues, which climate change may exacerbate (Semadeni-Davies, 2012), new management systems will need to be designed to contend with future climate change and may bring about new performance expectations unlike those in recent history (Milly et al., 2008).

Conventional drainage practice typically operate by catching all the runoff falling on rooftops, streets and pavements in urban areas and passing this water to storm sewers which is then passed to gully pots, pipes and finally the water treatment facilities prior to discharging it to local water courses. Conventional drainage practice tends to focus on managing water quantity, with less attention given to water quality, biodiversity and amenity (Charlesworth, 2010). As a result urban watercourses have become “neglected, abused or modified” (Keller and Hoffman, 1977, p. 237). Storm water runoff from urban areas including roads, car parks and roofs is a well-known cause of stream degradation or “urban stream syndrome” (Pyke et al., 2011). Conventional drainage practice, relying on rapid conveyance remains a relatively crude approach for managing urban water. Even in separate sewer systems where a dedicated pipe system exists; rapid conveyance can result in sudden flooding of the watercourse where the water is discharged (Jones and Macdonald, 2007). In addition, conventional drainage systems relying on combined pipe networks have been criticised for being both resource intensive and environmentally unsound (Butler and Parkinson, 1997).

4.2.5 Sustainable urban drainage systems (SUDS)

Sustainable urban drainage systems (SUDS) (known elsewhere as Best Management Practice or BMPs) are increasingly seen as a viable solution to the problems posed by future climate change. Unlike conventional drainage, SUDS typically operate by encouraging infiltration and detention on site, in many ways the opposite to conventional drainage practice which tends to treat water as “an embarrassment, to be hidden from sight and forgotten” (Charlesworth, 2010, p.166). SUDS on the other hand treat water as a “liquid asset” (Semadeni-Davies

et al., 2008) and are capable of decreasing peaks flows, increasing lag times and in turn reducing consequences associated with storm water flows. SUDS include a wide variety of both hard (above and below ground assets) and soft engineering solutions including green roofs, swales, filter strips, wetlands, detention basins, rain gardens, 'good housekeeping' and education (Woods-Ballard et al., 2007). The design and construction of these SUDS are beyond the scope of this thesis, readers are directed elsewhere for further details (Charlesworth et al., 2003; Castro Fresno et al., 2005; GDSDS, 2005; DTI, 2006; Woods-Ballard et al., 2007; SEPA, 2013). SUDS are designed to subvert the notion of rapid transit of urban runoff, encouraging the view that water is more acceptable in the city (Woods-Ballard et al., 2007). SUDS have the potential to be a "powerful weapon in the arsenal of techniques used to combat a changing climate" (Charlesworth, 2010, p.166). SUDS facilitate natural groundwater recharge, reduce flood risk and facilitate purification. By redirecting runoff away from impervious areas, SUDS also help to reduce inflow thereby reducing 'discharge throttling' at drain outlets (D'Arcy and Frost, 2001). By extending the lag time between periods of intense precipitation SUDS provide a buffer for sewer systems and natural watercourses, preventing them from being overloaded during periods of intense precipitation (Jones and Macdonald, 2007).

In addition, SUDS can "green and cool" urban areas, reduce the urban heat island effect (UHIE) and improve human health (Maas et al., 2006). The UHIE is a condition whereby urban areas can be several degrees warmer than surrounding areas even during cool months, the UHIE was first noted in 1819 in London (Authority, 2007) and has been noted to adversely affect human comfort and health (Coutts et al., 2013). One way to mitigate the UHIE is through the planting of vegetation in urban areas which can create an "oasis effect", in which temperatures are reduced near to vegetative areas (Charlesworth, 2010). In addition to storm water and UHIE benefits, vegetated SUDS can sequester carbon dioxide, thereby increasing house prices and lowering energy costs needed to heat and cool buildings (Tratalos et al., 2007). In the UK, where we typically spend more money heating buildings than cooling them, UHIE may be viewed as beneficial. However, the negative implications of the UHIE, particularly

for public health may well exceed the potential savings associated with heating buildings. For example raising the temperature above 25°C can lead to more summer deaths, in excess of 27°C, those individuals with impaired sweating mechanisms may find it increasingly difficult to regulate their own body temperatures. In 2006 in England, an estimated 75 extra deaths per week were estimated for each degree increase in temperature, as a result of pollution and the impact of heat on the cardiovascular system, particularly among elderly people (Public Health England, 2013). Furthermore, suicide rates have been shown to increase during heat waves in the UK (Public Health England, 2013). Many studies have been previously undertaken to analyse the carbon sequestration and storage of SUDS, with most focussing on the value of urban trees (Nowak and Crane, 2002; Pataki et al., 2006), constructed wetlands (Kayranli et al., 2010) and green roofs (Getter and Rowe, 2009). Carbon sequestration is however not limited to just vegetative devices, it has previously been suggested that the world's farm ponds capture more organic carbon in a year than the world's oceans (Downing et al., 2008). It has even been estimated that a 15 m² pond can capture the equivalent amount of carbon as trees with an area of 100 m² (Pond Conservation Org, 2013). As a result, SUDS incorporating a vegetative component such as ponds, swales and wetlands can help mitigate future climate change, by capturing excess anthropogenic carbon (Charlesworth, 2010). SUDS may be installed individually, although a more common practice and one that is now stipulated by new SUDS regulations is to use multiple SUDS together, more commonly referred to as a SUDS "treatment train". Many examples of SUDS treatment trains exist in the UK including the EA SUDS demonstration sites at Wheatley Motorway Services Area on the M40 (Bray, 2010) and Hopwood Motorway Services Area on the M42 (Heal et al., 2008) although they are not the focus of this research.

4.2.6 Urban runoff

The construction of SUDS requires careful planning and a consideration of the site characteristics to ensure they are fit for purpose. In the case of traditional drainage practice, the design standard is typically treated as the 1 in 30 year

event (Charlesworth, 2010). The UK is in the process of finalising the National Standards for Sustainable Drainage Systems which will lay out the requirements of SUDS for greenfield and brownfield sites. Similar policies are already in place elsewhere in the world such as Australia (Australian Government, 2009). In England and Wales, the Flood and Water Management Act 2010 stipulates that developments and redevelopments to prepare surface runoff drainage plans for approval by a SUDS Approving Body (SAB) where construction works may have implications for drainage. The National Standards for Sustainable Drainage Systems were designed to ensure surface runoff is managed at its source on the surface, public space is integrated with the drainage system where it is practical to do so and to ensure the system is cost-effective over its lifetime. In doing so, the drainage system design must account for changes in impermeable area and equally important climate change. It is vital that engineers and planners consider the impacts of climate change to ensure these systems perform adequately and provide reliable protection under future climate uncertainty, particularly for small, more frequent events for which SUDS generally perform very effectively (Charlesworth, 2010). Climate change can be considered by uplifting rainfall depths by an amount recommended by the EA, who has previously suggested using a value of 20% for extreme rainfall intensities based on the 2080s time slice (Woods-Ballard et al., 2007). Up until now, SUDS have been designed on the premise of preserving the pre-development hydrological regime. Typically this has been achieved by limiting site discharge to a specified rate, here defined using the Institute of Hydrology Report 124 (IH124) equation. Alternative greenfield runoff guidance estimation methods are available including ADAS Report 345 (ADAS 345), the Rational Method, Transport and Road Research Laboratory (TRRL) LR 565 method, Flood Studies based runoff equations (FSR) and in Northern Ireland the Poots and Cochrane equation. Debate regarding these methods is ongoing and to date no definitive agreement exists with regards to which method is best. Despite this, use of IH124 for greenfield runoff estimation has been previously been advocated in numerous reports (Balmforth et al., 2006; Woods-Ballard et al., 2007). The following reasons outlined in Kellagher, (2011) provide the main justifications for the use of the IH124 equation over the

alternative methods presented here, (1) the method is easy to use and can be applied nationally, (2) there are copyright issues regarding the Flood Estimation Handbook (FEH) parameters, meaning these tools would need to be purchased for these to be usable and (3) the implementation of the FEH and Revitalised Flood Hydrograph (ReFH) methods must be undertaken by a competent hydrologist for the results to be considered valid, which represents an additional expense and thus may not always be possible.

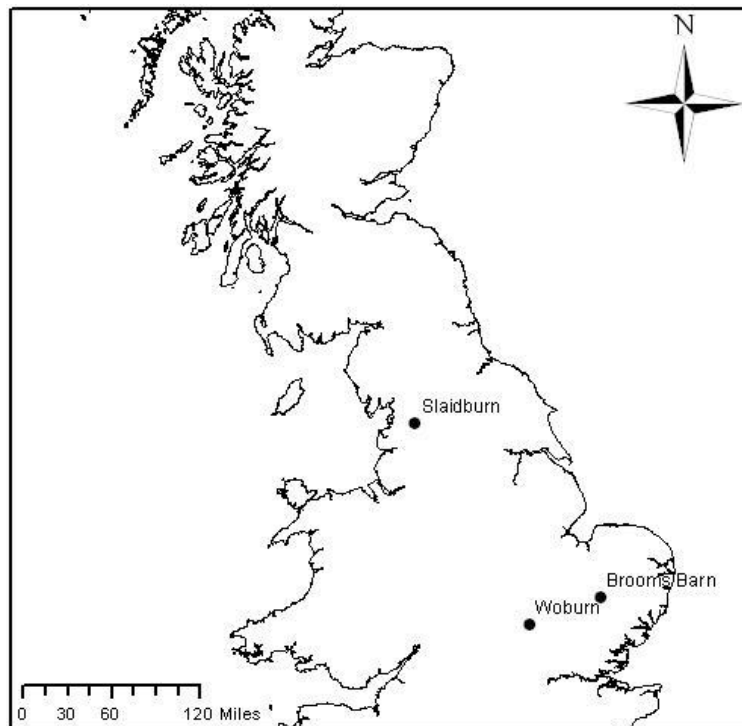
4.3 Methodology

4.3.1 Sites

A study by Hess, (2010) identified eleven meteorological stations, representing a range of agroclimatic conditions in England. Three of the original eleven sites were selected for further analysis, providing different agro-climatic conditions. Two sites are in the dry east of England, the most intensively farmed area for potatoes in the UK with the largest irrigation demand and one site is in the wet north of England for the purpose of comparison, where drainage is the bigger issue, due to elevated rainfall. Brooms Barn is located in the county of Suffolk, near Bury St Edmunds, approximately 30 km east of Cambridge and is the driest of the investigated sites. Slaidburn is located in the district of Lancashire, approximately 60 km north-west of Leeds and is the wettest site with an average annual rainfall of 1,515 mm for the baseline period. Lastly, Woburn is situated in the county of Bedfordshire, 50 km north-west of London and is marginally wetter than Brooms Barn but with slightly lower annual evapotranspiration. These particular sites were chosen on the basis of their varied climatology and the fact they have the most complete observed record for the baseline period. Observed climate data was extracted for the baseline period from the weather station at each site. Precipitation and reference evapotranspiration (ET_o) data for the baseline period is shown in Table 4.2 (Hess, 2010).

Table 4.2 Weather station sites and records use

Station	Lat.	Long.	Elevation (m AOD)	Average annual (1961-1990)		Data	
				Precipitation (mm)	ETo (mm)	From	To
Brooms Barn	52.260	0.567	75	588	585	1964	1990
Slaidburn	53.987	-2.433	192	1515	487	1961	1990
Woburn	52.014	-0.595	89	632	564	1961	1990



4.3.2 Climatology

Observed baseline climate data was downloaded from a weather station at each site, this data was obtained from the Met Office Integrated Data Archive System (MIADS) dataset, available via the British Atmospheric Data Centre (BADC). Several climate parameters are available, including precipitation, daily max temperature, minimum temperature, relative humidity, wind speed and sunshine hour data for each site. Duplicate and spurious data entries were removed prior to data processing. This climate data was used to calculate daily evapotranspiration for the baseline period using the equations set out in Penman-Monteith (Monteith, 1965), using the freely available tool WaSim ET, accessible via the Cranfield University website.

All 10,000 monthly change factor climate projections were extracted from the UKCP09 sample ensemble for a single 25 km² grid square overlying each weather station, for each of the emission scenarios (i.e. low, medium and high) for the 2050s time slice i.e. 2040-2069. The 2050s was selected as the desired time slice because (1) it reflected the typical lifetime of the assets considered here and (2) is subject to considerable uncertainty. Monthly evapotranspiration change factors were similarly estimated using Penman-Monteith (Monteith, 1965); wind speed was assumed to be the same as the observed baseline (1969-1990) due to the lack of earlier baseline data and future projections of wind speed.

For reasons that will be made clearer in CHAPTER 6, ten thousand climate projections were simultaneously generated using the UKCP09 Weather Generator (WG), using the same projection ID codes to allow direct comparison, again for grid squares overlying each weather station and each emissions scenario. As the UKCP09 WG offers a much greater spatial resolution of 5 km², data was generated for a grouping of 25 individual grid squares, i.e. a combined area of 25 km², overlying each weather station, to be directly comparable with the 10,000 sample ensemble 25 km² grid square. The UKCP09 WG was previously found to be reasonably calibrated at the investigated sites with the exception of some extreme events which were beyond the scope of our analysis and do not impact the reservoir design but may have significant implications for SUDS design.

It should be noted that the UKCP09 WG and 10,000 sample ensemble spatial grids differ slightly in their orientation which may create subtle differences in the projected climate, though because of the large areas used, the impact is considered somewhat negligible. Despite this, the uncertainties introduced by these subtle differences are an acknowledged limitation of this research.

4.3.3 WaSim model description

Downscaled climate change projections from UKC09 can be fed into the impact model WaSim. WaSim is a one-dimensional daily, soil water balance capable of simulating soil water storage, infiltration and evapotranspiration and drainage of water in response to climate, irrigation and seepage where relevant (Hess and

Counsell, 2000). WaSim has proven invaluable across a range of previous studies including determining irrigation requirements, optimising water management, assessing the performance of sub-surface drainage systems and studying the effects of climate change on water resources e.g. Depeweg and Fabiola Otero, (2004), Hirekhan et al., (2007) and Warren and Holman, (2012). Guidance values covering crop development and root depths are provided for selected crops within WaSim, and up to three crops can be combined in a cropping pattern (Hess and Counsell, 2000). WaSim divides the soil profile into five layers, water moves from upper layers to lower layers when the water content of the respective layer exceeds field capacity. The first three layers are comprised of the surface layer (0 - 0.15 m), the active root zone layer (0.15 m - root depth) and the unsaturated layer below the root zone (root depth-water table). The remaining two layers are comprised of the saturated layer above drain depth (water table – drain depth) and the saturated layer below drain depth (depth drain – impermeable layer). The boundary between the second and third layers changes in response to root growth (e.g. in the case of potatoes, layer 2 has zero thickness when root depth is less than 0.15 m, and then increases as the potato develops). The daily percentage crop cover is determined by linear interpolation between the dates of emergence, 20% cover, maximum cover, maturity and harvest. Senescence is simulated by linear interpolation in crop cover between maximum cover at maturity and zero at harvest (Hess and Counsell, 2000). Surface runoff is comprised of saturation and infiltration excess runoff, the latter is estimated using the Soil Conservation Service (SCS) curve number method. Precipitation that does not contribute to runoff, is assumed to infiltrate. Actual evapotranspiration is estimated using the weighted average of crop transpiration and soil evaporation. Plant transpiration is calculated as a proportion of reference evapotranspiration on the basis of the plant type and soil water content (Allen et al., 1998). As a result it does not consider the effect of raised atmospheric carbon dioxide (Gedney et al., 2006). A schematic diagram of WaSim is provided in

Figure 4.1.

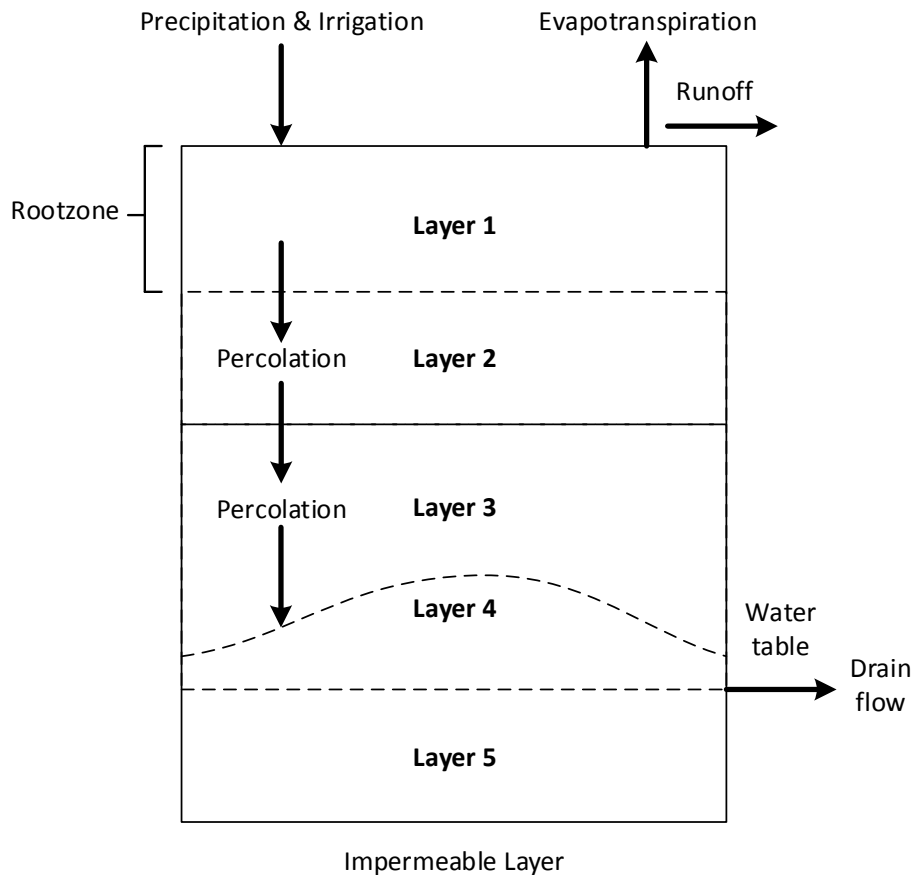


Figure 4.1 WaSim schematic diagram (adapted from Hess and Counsell, 2000)

4.4 Irrigation reservoir

4.4.1.1 Calculating irrigation demand

Next, WaSim was used to model irrigation demand at each site. In its basic format WaSim is not capable of processing multiple climate files succinctly, so a modified version was developed and employed for this study to read-in multiple climate files and output a single results file containing the daily irrigation demand for each of the 10,000 climate files. A potato crop was simulated with a planting depth of 0.15 m, max root depth of 0.7 m and planting date of 1st April. A rule based irrigation schedule was modelled based on best practice guidelines including scab control (Defra, 2005). This schedule consisted of 4 periods, 1 non-irrigation followed by 2 irrigation and 1-non irrigation, applying 15 mm of water early in the growing season whenever the root zone deficit exceeded 18 mm during period 2

(15th May - 30th June) and applying 25 mm of water whenever the root zone deficit exceeded 30 mm during period 3 (30th June - 31st August). The soil type was set as sandy loam, which is the dominant soil type for potato crops in England, with an assumed saturation of 43.3% and field capacity of 24.5%. The irrigation demand was calculated for each year in the 10,000 x 30 year sequences for each site and emission scenario, using both the change factor and UKCP09 WG datasets.

4.4.1.2 Cost benefit analysis

Next, typical costs and benefits for clay agricultural reservoirs were obtained from a concurrent study (Weatherhead et al., 2008). The economic benefit of the water contained within each reservoir was calculated on the basis of average water use, assuming an average net benefit (for potatoes) of £1.56.m⁻³ of water used (Morris et al., 1997) This value is consistent with more recent modelled results which estimated the yield and quality benefits of water to be in the region of £1.34 to £1.64.m⁻³, despite the yield value of potatoes rising in recent years (Morris et al., 2011). Earthwork costs were assumed to be £1.13.m⁻³ of earth moved, plus an additional 15% reflecting site investigation costs. A further £20 k was added, representing the assumed connection costs of 3-phase electricity. Annual operating expenditure (OPEX) was assumed to be 1% of capital expenditure (CAPEX), representing the low maintenance cost of clay reservoirs (Weatherhead et al., 2008). CAPEX and OPEX of various reservoir capacities are shown in Figure 4.2.

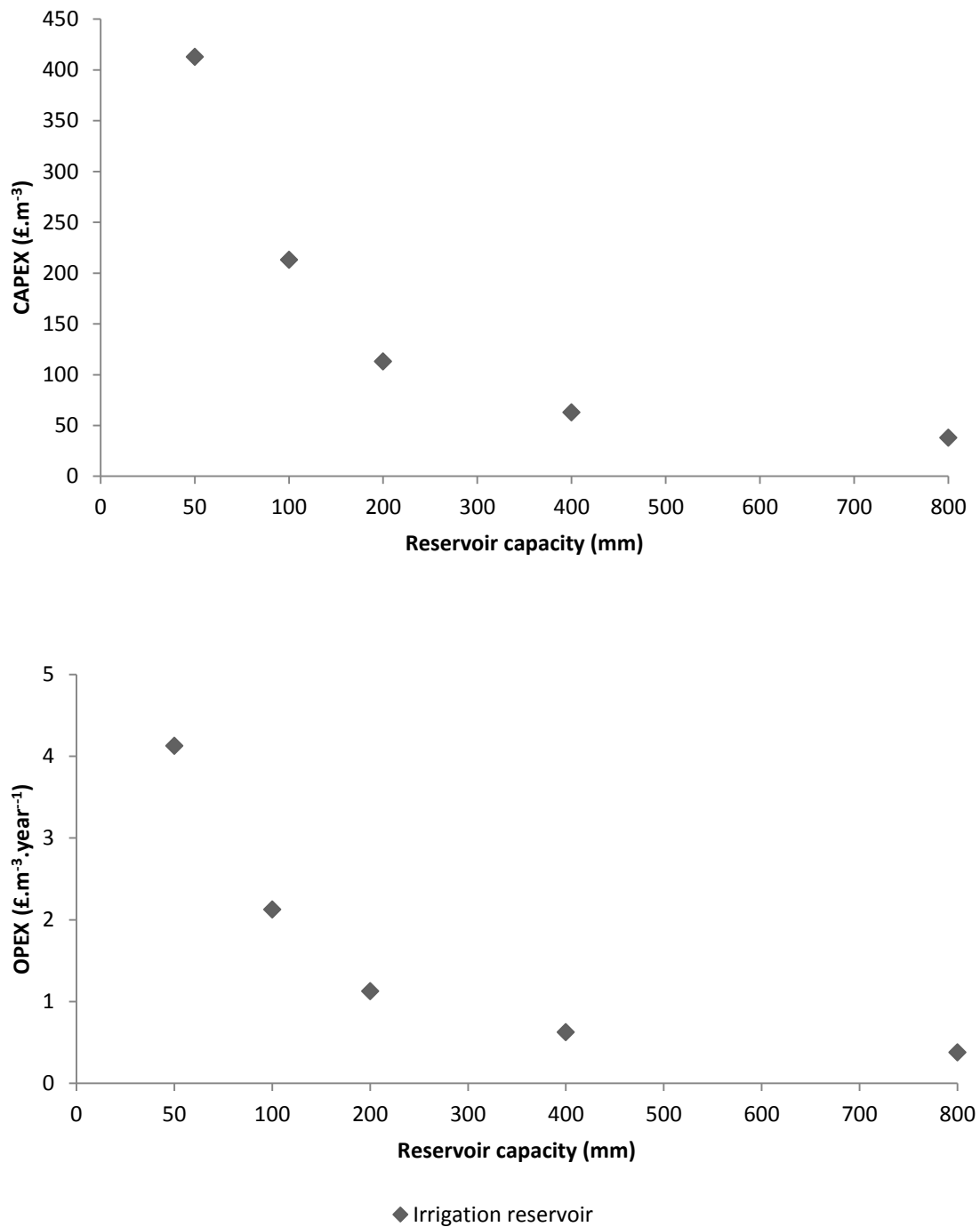


Figure 4.2 Irrigation reservoir CAPEX and OPEX £.m⁻³ reservoir capacity. Unit costs obtained from Weatherhead et al., (2008).

The observed baseline and each of the 10,000 sequences was then used to calculate the net present value (NPV) of a range of reservoir sizes, with usable storage capacities equivalent to 0 to 1,000 mm over the area irrigated (i.e. 0 to

10,000 m³.ha⁻¹). NPV provides a measure of the present value of the difference between the assumed costs and benefits of a decision. NPV was selected over other economic metrics because it is the primary criterion for deciding whether government action can be justified (Treasury, 2003). NPV was calculated by discounting the annual net benefit of the reservoir less OPEX costs with a lumped (non-discounted) CAPEX in year 0, assuming current government discount rate guidelines of 3.5% on investments of up to 30 years (Treasury, 2003). Each reservoir was assumed to last 30 years, representing their typical life cycle. Finally, the optimum reservoir capacity, defined as the size providing the highest NPV was calculated for each of the 10,000 sequences. A schematic diagram of the steps taken to produce the future series is shown in Figure 4.3.

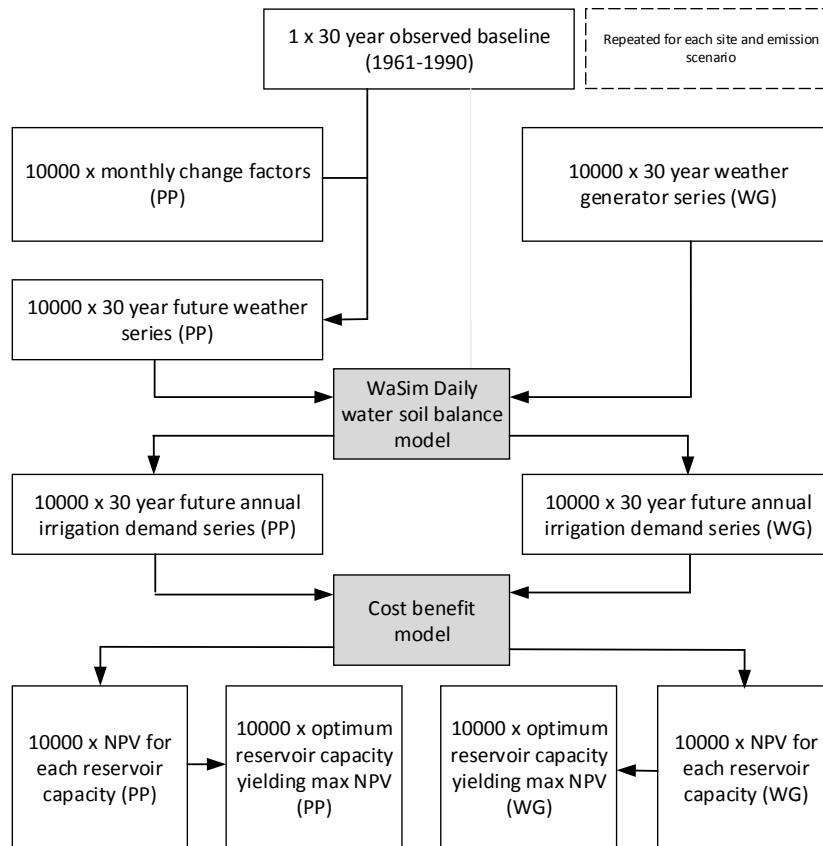


Figure 4.3 Irrigation reservoir series creation schematic diagram. ¹

4.5 SUDS

4.5.1 Calculating runoff from the total development

A series of hypothetical new developments were designed at the investigated sites, each with an area of 10 ha. It was assumed that these developments were comprised of 80% impermeable hard surface i.e. roads, roofs, pavement etc. and

¹ An observed baseline daily series was perturbed using monthly change factors from UKCP09 to produce 10,000 future daily climate series, these series were then fed into WaSim and the resulting outputs used as input data for a cost benefit model to determine the optimum reservoir capacity. Similarly, the future daily UKCP09 WG series were fed into WaSim and the resulting outputs used as input data for a cost benefit model to determine the optimum reservoir capacity.

20% permeable green space i.e. permanent grass. Runoff was calculated for the impermeable areas and permeable areas separately and the results combined to calculate the maximum daily runoff for each year in the 30 year observed baseline and 10,000 x 30 year sequences for each site and emission scenario, using both the change factor and UKCP09 WG datasets.

4.5.2 Calculating runoff from the impermeable areas

In order to calculate the volume of runoff produced from impermeable areas, depression losses were assumed, which accounts for rainfall that becomes trapped in small depressions on the catchment surface. Numerous factors can affect the degree of depression storage including surface type, slope and return period (Kidd and Lowing, 1979). Typical values for depression storage are 0.5-2mm for impervious areas, 2.5-7.5 mm for flat roofs, and up to 10 mm for gardens (Butler and Davies, 2004), a value of 2mm was used here. The effective rainfall i.e. rainfall – depression storage was calculated and multiplied by 60%, representing the percentage surface connectedness and 80% representing the percentage of the development that was impermeable, this value was then multiplied by the total development area of 10 hectares to estimate the volume of runoff (m³) from the impermeable part of the development. A value of 60% percentage surface connectedness was assumed on the basis of Osborne, (2001), which estimated the following values, based on the assumption that only a proportion of the impermeable area generates 100% runoff (Table 4.3). This was repeated for each site and emission scenario using both the change factor and UKCP09 WG datasets.

Table 4.3 Percentage surface connectedness (Adapted from Osborne, 2001)

Surface type	Percentage connected
Normal urban paved surfaces	60
Roof surfaces	80
Well-drained roads	80
Very high-quality roads	100

4.5.3 Calculating runoff from the permeable areas

WaSim was altered to output a single results file containing the daily runoff depth produced from the permeable part of the development. Permanent grass was simulated; the soil type was selected based on site characteristics. The dominant soil type at Brooms Barn is loam, at Slaidburn it is clay loam and at Woburn it is sandy loam (Land Information System, 2014). Permeable runoff was calculated using the SCS method. This particular daily runoff model was chosen because (1) SUDS are typically designed to drain down within 24 hours (Woods-Ballard et al., 2007), (2) to support the direct comparison of the UKCP09 change factor and UKCP09 WG datasets, the former of which is limited to a daily resolution and (3) it is the runoff methodology used by WaSim and thus reduced the possibility of introducing additional model uncertainties. Readers are directed to Hess and Counsell, (2000), for details of its calculation. For each site, the daily runoff (mm) obtained using the SCS method was multiplied by 20% representing the percentage of the development area that was permeable; this value was then multiplied by the total development area of 10 hectares to estimate the volume of runoff (m^3) from the impermeable part of the development. This was repeated for each site and emission scenario using both the change factor and UKCP09 WG datasets.

4.5.4 Cost benefit analysis

Next, typical costs and benefits for a range of SUDS and traditional drainage devices (i.e. concrete storage tanks) were obtained from a recent cost-benefit analysis study (SEPA, 2013). CAPEX and OPEX for various SUDS and traditional drainage devices are shown in Figure 4.4.

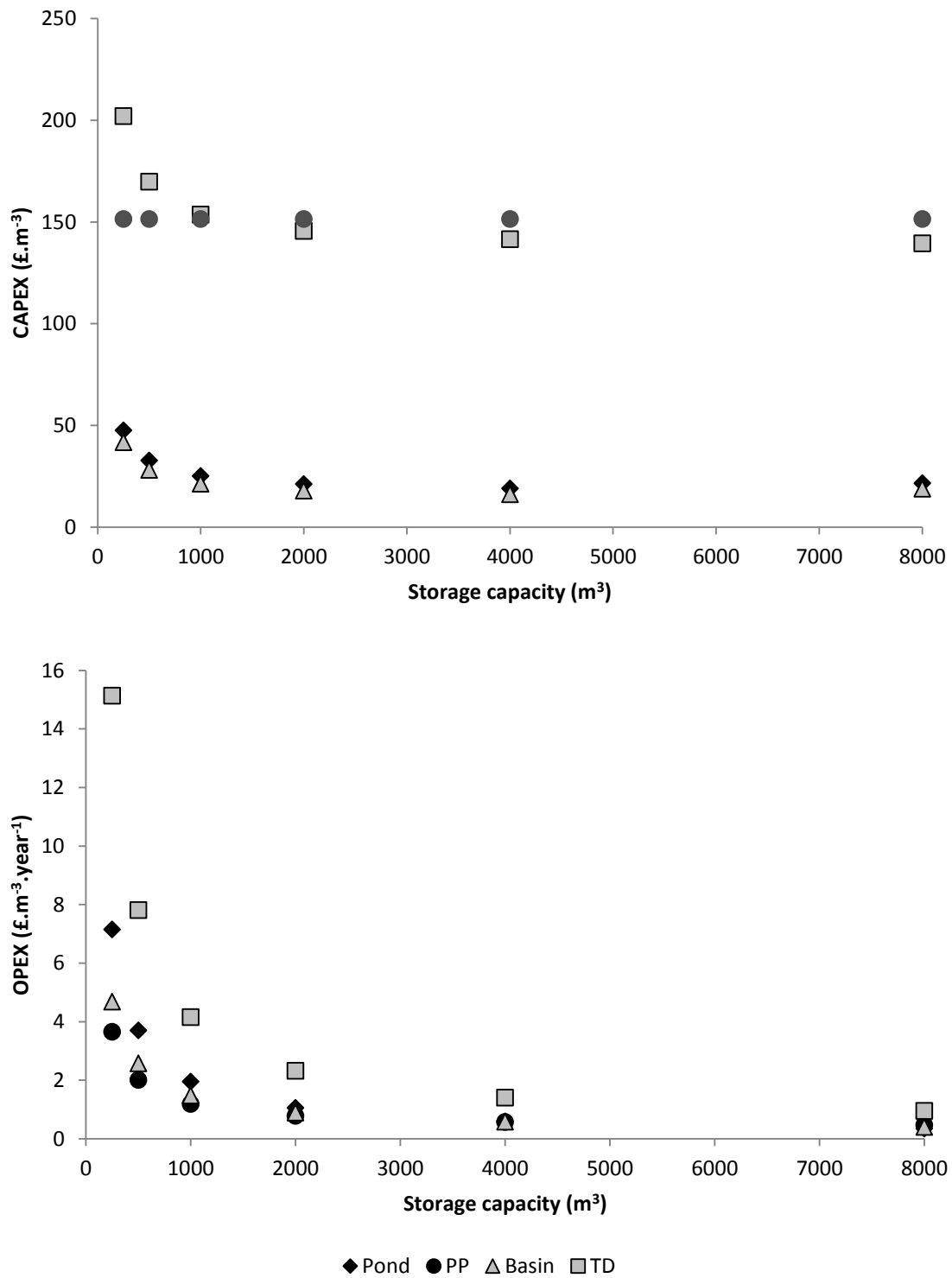


Figure 4.4 SUDS and traditional drainage (TD) CAPEX and OPEX £.m-3 storage capacity. Unit costs obtained from (Duffy et al., 2008) and (SEPA, 2014) and converted to 2013 prices using (Department for Business, Innovation and Skill, 2014)

SUDS costs were converted to 2013 prices using the Department for Business, Innovation and Skill, All New Construction Index and All Repair & Maintenance Index (Department for Business, Innovation and Skill, 2014). Traditional drainage device costs were obtained from equations found in Duffy et al., (2008) and similarly converted to 2013 prices. For ponds, CAPEX was calculated on the basis of topsoil excavation, bottom soil excavation, deposition of excavated material assuming 80% recovery, 20% deposition offsite, embankment construction costs, submerged berm construction costs, topsoil application, liner installation, vegetation installation, inlet and outlet construction in addition to an assumed land take cost for excessively large SUDS. Land take costs were estimated on the basis of the UK average residential land value of £208.65.m⁻² (Valuation Office Agency, 2014). It was assumed that ponds and basins are typically constructed using existing green spaces. However for the purpose of this research, an imposed limit was used to discourage building excessively large SUDS in line with new development guidelines. New developments are encouraged to incorporate green space within the development area. Twenty percent of the development areas were comprised of permeable areas and not available for hard surfaces e.g. roads, pavement, buildings etc. It was conservatively assumed that only 25% of the permeable areas of the development equivalent to 5% of the total development area was directly available for SUDS construction, anything in excess of this would incur an additional land take costs for every m² of additional land occupied, charged at a fixed rate based on the residential land value. In reality this value is somewhat conservatively low, as SUDS are typically designed to be dual-purpose, providing attenuation as well as recreation facilities.

In the case of ponds, OPEX was comprised of inspection and monitoring, litter removal, grass cutting, hand cutting submerged plants and an annual “spring tidy”. Basins differ to ponds because they do not require a liner or planting of submerged plants, but do require weed control and scrub clearance. Permeable pavement CAPEX, on the other hand includes excavation, deposition of excavated material in addition to liner installation, paving, bedding layer installation, sub-surface installation and geo-textile installation (SEPA, 2014).

Permeable pavement OPEX consists of inspection and monitoring, weed control and an annual vacuum sweep to remove accumulated sediment from between paving slabs. As a result, permeable pavement tends to be considerably more expensive than an equivalent pond/basin providing the same storage, although for the purpose of this research it was assumed that permeable pavement does not incur land take costs because the asset itself is underground.

The benefits of SUDS are decidedly more complex to estimate than the benefits of irrigation reservoirs though numerous attempts have been made (see Susdrain, 2013 for an extended list of examples). In order to estimate the benefit of SUDS it is first necessary to estimate the capacity of SUDS required from a compliance perspective based on existing conditions. HR Wallingford have previously developed a paper method and an online storage estimation tool using the IH124 and FEH equations and a series of lookup tables to estimate the required storage capacity and thus an estimate of the costs and space needed (Kellagher, 2011). It is important to stress that the tool provides merely a storage approximation and should not be used to design complex drainage systems, however for the purpose of this research it was deemed appropriate. The online tool and accompanying report is founded on the principle that stormwater runoff discharged from urban developments should approximate to the greenfield runoff rate over an extended range of storm return periods as well as manage runoff on site for extreme events (Kellagher, 2011). This estimation tool uses a series of empirically based greenfield runoff-storage estimation curves to calculate the volume of storage required. Further details can be found online (Kellagher, 2011) and in the Defra report which accompanied the project (Kellagher, 2011).

The online tool provides numerous outputs, one of which is the attenuation storage based on the 1, 30 and 100 year events (Table A-1). Attenuation storage is used to ensure that the rate of runoff from a developed site to a receiving watercourse is limited to an acceptable rate, thereby reducing erosion and flooding downstream. Attenuation storage is calculated as a function of the degree of development relative to the greenfield discharge rate. An adjusted attenuation storage volume based on **only** the 1 and 30 year events can be

estimated using a series of linear regression equations, derived using curves found in the accompanying Defra report (Kellagher, 2011). The 1 in 1 year event, equivalent to a 100% annual exceedance probability, was selected to ensure the flow to receiving watercourses was tightly controlled to maintain natural channel morphology. The 1 in 30 year event, equivalent to a 3.33% annual exceedance probability, is important because of its strong links with the level of service required by sewers for adoption 7th edition (SfA7). SfA7 stipulate that sewers should be capable of carrying the 3.33% annual probability event within the system without causing flooding to any part of the site. An implied benefit value £.m⁻³ of water stored, was calculated based on the assumption that the NPV of the benefits of traditional drainage devices providing ample attenuation storage is equal to the NPV of the costs over the 30 year observed baseline period. In reality, the cost of building a traditional drainage device such as a concrete tank may not equal the benefits of storing the runoff produced during these high frequency events, however for the purpose of this research, this implied benefit value provided an assumed approximation of the benefit value per m³ of water stored. In contrast to traditional drainage devices, SUDS provide additional benefits not provided by traditional drainage devices, benefits that are inherently difficult to quantify such as those linked to public health and house prices, though the latter can be estimated using hedonic pricing methods (Pearson et al., 2002). Assuming a fixed benefit per m³ of water stored by traditional drainage devices and SUDS provided a useful basis on which to compare these assets. The implied benefit values per m³ of water stored of the three investigated sites, using traditional drainage devices and SUDS is shown in Table 4.4.

Table 4.4 Implied benefits (£.m⁻³) of traditional drainage devices (TD) and a range of SUDS including ponds, basins and permeable pavement. Implied benefit assuming that the NPV of the costs of the asset equal the NPV of the benefits of the asset.

Site	TD (i.e. concrete tank, bigger pipes)	Pond	Basin	Permeable Pavement
Brooms Barn	13.31	3.07	2.54	11.19
Slaidburn	10.49	2.33	1.95	9.06
Woburn	14.11	2.99	2.55	12.53

The results would suggest that the current SUDS standards in their current format, place a potentially inconsistent value on the benefit of water stored, though this result is subject to the model and assumptions used. Secondly, the derived benefit value of traditional drainage devices was reasonably consistent for the three investigated sites ranging between £10.49-14.11.m⁻³, and as a result an average value of £13.m⁻³ was chosen for simplicity and consistency to value the implied benefit of storing the water at all of the investigated sites. This course of action was taken as SUDS are increasingly seen as an alternative to traditional drainage devices and as a result it was assumed that they provide similar benefits in terms of the value of water stored. A core assumption of this model is that increasing the size of the SUDS increases the amount of and value of water stored, but also resulted in larger CAPEX and OPEX, thereby changing the optimum capacity depending on the severity of the runoff event associated with future climate change.

Next, each of the 10,000 climate sequences was used to calculate the NPV of a range of SUDS and traditional drainage devices sizes, with usable storage capacities equivalent to the adjusted attenuation storage calculated using **only** the 1 and 30 year events (Table 4.5) with an additional storage capacity of between 0-5,000m³ for the purpose of managing runoff created by future climate change.

Table 4.5 Attenuation storage based on 1, 30 & 100 year event and 1 & 30 event

Site	Attenuation storage (1,30 & 100 year) (m ³)	Adjusted attenuation storage (1, 30 year) (m ³)
Brooms Barn	1770	1500
Slaidburn	1880	1800
Woburn	1880	1800

NPV was again calculated by discounting the annual net benefit of the SUDS and traditional drainage devices based on the assumed value of £13.m⁻³ loss OPEX costs with a lumped (non-discounted) CAPEX in year 0, assuming current government discount rate guidelines of 3.5% on investments of up to 30 years (Treasury, 2003). Each of the SUDS and traditional drainage devices was assumed to last 30 years, representing their typical life cycle. Finally, the optimum capacity of each of the SUDS and traditional drainage devices, defined as the capacity providing the highest NPV was calculated for each of the 10,000 sequences. A schematic diagram of the steps taken to produce the future series is shown in Figure 4.5.

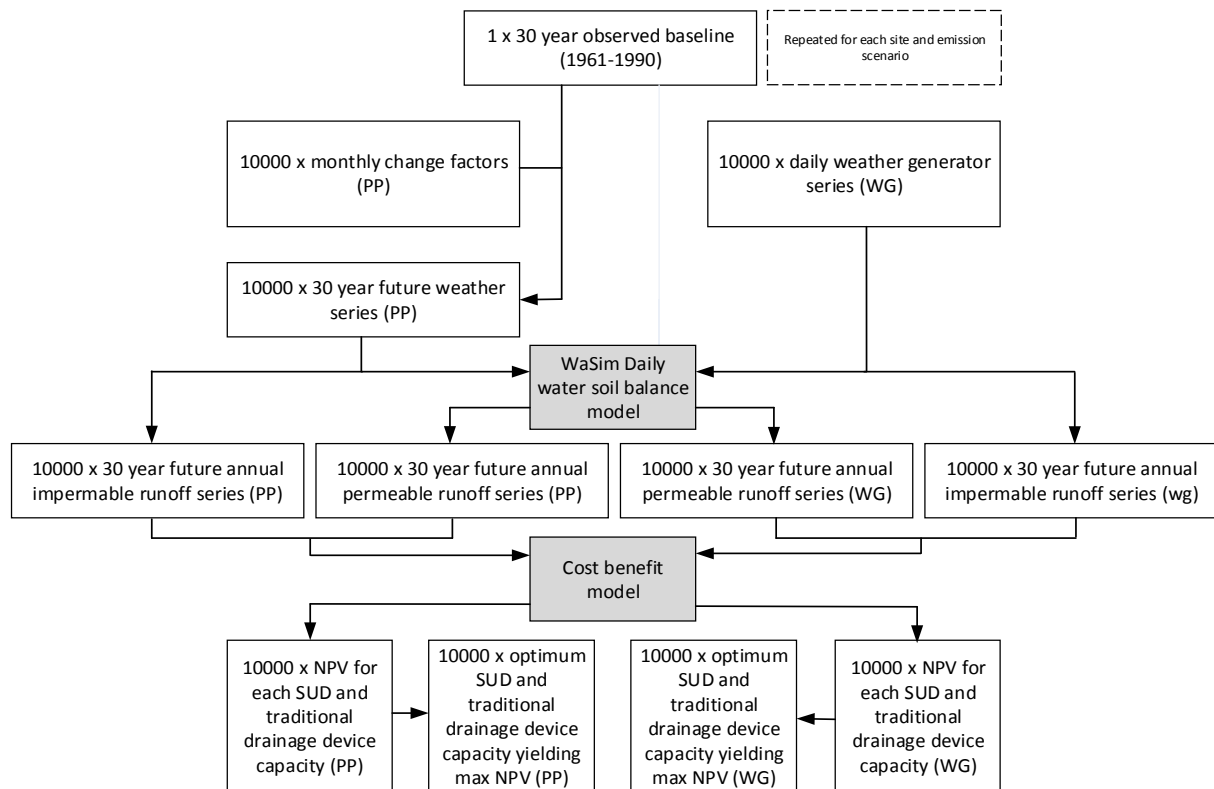


Figure 4.5 SUDS series creation schematic diagram irrigation reservoir series creation schematic diagram. An observed baseline daily series was perturbed using monthly change factors from UKCP09 to produce 10,000 future daily climate series, these series were then fed into WaSim and the resulting outputs used as input data for a cost benefit model to determine the optimum SUDS capacity. Similarly, the future daily UKCP09 WG series were fed into WaSim and the resulting outputs used as input data for a cost benefit model to determine the optimum SUDS capacity

4.5.5 Model output analysis

The irrigation reservoir and SUDS capacities obtained using the above methodologies, calculated using different emission scenarios, datasets, the complete probabilistic dataset, sub-samples of it and different decision criteria are compared in subsequent chapters. The combined results of which are presented and discussed in more detail in CHAPTER 8 in order to identify those factors and choices that have the largest impact on decision making for local water management.

CHAPTER 5. PROJECTIONS: A SYSTEMATIC COMPARISON

5.1 Overview

This chapter begins by discussing the merits and limitations of the 11SCP and 10,000 sample ensemble. The move from deterministic and probabilistic climate change projections and its implications for decision making is discussed. Next, simple random and Latin hypercube sampling versus using the complete probabilistic is discussed. Results for two case studies at three UK sites using all three emission scenarios, using the 11SCP, probabilistic projections, deterministic projections and sub-samples of the complete probabilistic dataset for the 2050s are summarised and their impact on decision making for local water management is explored.

5.2 Background

5.2.1 Introduction

Climate change projections are increasingly being presented in terms of uncertainties and probability distributions rather than median or “most-likely” values. UKCP09 provides 10,000 probabilistic projections via the 10,000 sample ensemble and 11 spatially coherent projections via the 11SCP, for three future emission scenarios. In contrast, previous iterations such as UKCIP02 provided only a single “most-likely” (deterministic) projection for each. This move from deterministic to probabilistic methods of communicating climate change information, whilst increasing the wealth of the data, complicates the process of adaptation planning by communicating extra uncertainty to the public and decision makers that may be unfamiliar with it.

Decision makers are increasingly looking to scientists for information about the likelihood of future climate change. Traditionally, science has proved invaluable to decision makers, either by providing accurate predictions or by enabling technological advancements which have enabled decision makers to “steer” the future toward desired outcomes (Dessai et al., 2009). Unfortunately, there are many examples, of which climate change is an example, where the science has

not been as forthcoming as decision makers had hoped (Millner, 2012). Scientists, correctly and arguably, emphasise the uncertainties, while decision makers seek a clear picture. As a result, a large disparity has begun to emerge between what decision makers want and what scientists can reasonably provide.

Recent advances in computational power have allowed for partial quantification of model uncertainty including perturbed physics ensembles (Stainforth et al., 2005), multi-model ensembles (Tebaldi and Knutti, 2007) and advanced statistical techniques (Rougier and Sexton, 2007) on which UKCP09 is founded.

5.2.2 Deterministic and Probabilistic climate change projections

In recent years, a move from deterministic to probabilistic methods of communicating climate change information and uncertainty has been observed, though how the latter should be interpreted is an area of continuing debate (Stainforth et al., 2007). Expressing climate change as a range of potential outcomes as opposed to a single value in itself increases the complexity. The move from deterministic methods of communicating climate change information (e.g. UKCIP02) to probabilistic methods (e.g. UKCP09) may be viewed as a 'conceptual leap' and has forced many decision makers to reassess how they use climate change information to inform policy (Harris et al., 2012; Weaver et al., 2013). Prior to the release of UKCP09, in the UK decision makers were largely reliant on UKCIP02 and other non-probabilistic climate change projections. In strong contrast to UKCP09, UKCIP02 was derived from Regional Climate Model (RCM) simulations. The UKCIP02 projections were spatially and temporally coherent for all climate variables and therefore could be used to assess climate change impacts at multiple locations in a spatially coherent way.

Two datasets, both available via the UKCP09 user interface, the UKCP09 sample ensemble and 11SCP are used here to model the impact of climate change on irrigation reservoir and SUDS design. Both datasets used the change factor approach to generate future projections at a daily resolution (Table 5.1), the implications of using an alternate downscaling approach are explored in CHAPTER 6. These particular datasets were chosen to enable the comparison

of different climate projection datasets, considering different sources and degrees of uncertainties, whilst preserving the same downscaling approach.

Table 5.1 Summary of downscaling methods considered

Dataset	Downscaling method	Sample Size	Description
UKCP09 sample ensemble	Change factor	10,000	1 x Observed baseline (1961-1990) perturbed using 10,000 sets of monthly change factors (PE changes not available so estimated using Penman-Monteith)
11SCP	Change factor	11	1 x Observed baseline (1961-1990) perturbed using 11 sets of monthly change factors (PE changes not available so estimated using Penman-Monteith)

5.2.3 UKCP09 sample ensemble

The UKCP09 sample ensemble provides monthly change factors and absolute values for grid cells covering a 25 km x 25 km area for any location in the UK, as well as 16 administrative regions and 23 river basin regions (Murphy et al., 2009). Sub-samples of the full UKCP09 sample ensemble can be requested, using random selection or specified using sample IDs. The full UKCP09 sample ensemble i.e. all 10,000 projections for an individual grid square at each site was used here for completeness. It is important to stress that the projections underpinning the sample ensemble are not spatially coherent, i.e. the n^{th} line of change factors from a grid square do not correspond to the n^{th} line of change factors for any other grid square. This is because of the methods used to create the UKCP09 probabilistic projections required the use of statistical emulators. As a result of the limitations in computing power and statistics techniques available at the time of producing UKCP09, climate variables had to be processed in small subsets meaning fully spatially coherent projections could not be produced (Sexton and Murphy, 2010). Furthermore, the climate variables contained within the sample ensemble dataset were produced in two batches and the data is not

coherent between batches (Murphy et al., 2004). That is the n^{th} line of change factors from batch 1 do not correspond to the n^{th} line of change factors from batch 2. As a result, evapotranspiration calculations requiring surface radiation data cannot be applied in the standard way, as temperature data is located in batch 1 whereas short wave and long wave radiation fluxes are located in batch 2 (Murphy et al., 2009). Formulations using cloud, temperature, wind speed and relative humidity can however be applied as was done so here to produce evapotranspiration change factors using Penman-Monteith (Monteith, 1965), solely temperature based formulations can also be applied although were not used here (Oudin et al., 2005; Kay and Jones, 2012). Despite the lack of spatial coherence, the UKCP09 sample ensemble can still support regional and even national assessments. For example, multiple variables can be analysed individually and the results pooled to produce maps. This approach effectively treats the variables as independent of each other, though this remains valid only if the potential impacts identified from these maps are treated separately and not coherently i.e. while impacts at one or more locations may occur in the future, they might not necessarily occur at the same time (Sexton and Murphy, 2010).

5.2.4 11SCP Spatially Coherent Projections

The 11SCP, in contrast to the UKCP09 sample ensemble, are only available as pre-generated datasets located in the UKCP09 csv archive accessed via UKCP09 user interface. The 11SCP were created by applying scaling factors to 11 regional climate models (11RCM) with the aim of incorporating the wider uncertainties considered by UKCP09. However while the 11SCP are considered to be equi-probable, the 11SCP projections are not probabilistic in nature and so do not replicate the breadth of uncertainty considered by the UKCP09 sample ensemble. UKCIP have been clear to stress that the 11SCP are not a replacement for the sample ensemble (Sexton and Murphy, 2010), despite this, some users may purposely use them, even for single grid squares, because the resources required to process and interpret the outputs from the 11SCP are much smaller.

The 11SCP provides monthly change factors and absolute values for grid cells covering a 25 km x 25 km area for any location in the UK. However unlike the sample ensemble dataset, the 11SCP are spatially coherent, that is the n^{th} line of change factors from a grid square do correspond to the n^{th} line of change factors for any other grid square. Unlike the sample ensemble dataset, this 11SCP can be used to model changes in different parts of a large catchment simultaneously using a semi-lumped model (Kay and Jones, 2012). The 11SCP were originally developed with three goals in mind. The first was to provide projections for all three emission scenarios similar to the sample ensemble, the second to satisfy user requirements for a “small sample size”, using fewer projections that are easier to use for decision making where multiple variables must be considered. Lastly, the 11SCP were designed to be spatially coherent, like the 11RCM used to create them, whilst still considering some of the uncertainty communicated by the UKCP09 probabilities projections, with particular reference to the spread of projections (Sexton and Murphy, 2010).

An extensive discussion of the merits and weaknesses of 10,000 sample ensemble dataset and 11SCP dataset can be found elsewhere and in greater detail (see for example Sexton and Murphy, 2010). However a summary table, outlining the main advantages, disadvantages is provided in Table 5.2 along with a short discussion.

Table 5.2 Advantages and disadvantages of UKCP09 sample ensemble and 11SCP

UKCP09 sample ensemble	
Advantages	<p>Provide probabilistic projections of future climate change, enabling risk-based climate change impact assessments to be undertaken.</p> <p>Provide 10,000 equi-probable absolute and change factors for multiple time slices and three emission scenarios.</p> <p>UKCP09 outputs can be visualised in many different ways including maps, graphs or raw data via the user interface.</p> <p>Considers uncertainties associated with the HADCM3 GCM, including important climate feedback processes such as the carbon and sulphur cycle in addition to ocean physics.</p> <p>Projections include information from other GCMs, twelve other climate models used in the IPCC fourth assessment report were incorporated into UKCP09, thereby capturing model structure uncertainty.</p> <p>Projections are provided for 25km grid square and several pre-defined aggregated areas including administrative regions and river basins. Probabilistic projections are also provided for some marine regions around the UK.</p>
Disadvantages	<p>Processing all 10,000 projections is time-consuming and can be resource intensive.</p> <p>Certain climate variables e.g. wind speed are not available.</p> <p>Does not consider certain feedbacks such as climate-methane cycle because their effects are considered to be small or they are not fully understood.</p> <p>Projections are not provided at daily or hourly time scales, projections can be temporally and spatially downscaled although this can introduce additional uncertainties.</p> <p>Uncertainties stemming from emission scenarios are not explored in probabilistic terms, emission scenarios are provided which explores uncertainty in a limited capacity.</p> <p>Climate variables from multiple grid squares cannot be averaged as the projections are not spatially coherent.</p> <p>Does not provide a smooth trajectory of climate change projections through the 21st century.</p>

11SCP

Advantages	<p>Provide spatially coherent projections, allowing assessments to be undertaken where multiple sites are concerned, such as modelling river catchments.</p> <p>Climate variables from multiple grid squares can be averaged as the projections are spatially coherent.</p> <p>Projections are fewer in number (n=11) and therefore easier to interpret.</p> <p>Provides a larger number of climate variables compared to the sample ensemble, such as wind speed.</p> <p>Consider a wider range of uncertainty compared to the 11RCM, though not as much as the UKCP09 sample ensemble.</p>
Disadvantages	<p>Do not consider uncertainty stemming from atmospheric processes, carbon cycle, sulphur cycle or ocean physics.</p> <p>Do not provide a smooth trajectory of climate change through the 21st century.</p> <p>11SCP cannot be used to drive the UKCP09 WG, the UKCP09 sample ensemble and 11SCP were generated using very different methods and as a result the results should not be combined.</p> <p>The 11SCP outputs are only available in a .csv format, UKCP09 does not provide maps or graphs, and also the outputs are hidden beneath the UKCP09 user interface and may be less obvious from the perspective of a new-user.</p>

The main advantage of the 11SCP, over the sample ensemble dataset, is that they provide spatially coherent projections which allows decision makers to undertake assessments where multiple locations are concerned (in a spatially coherent way) as well as provide insight into how different climate variables interact with each other. The main disadvantage of the 11SCP is that they do not consider structural uncertainty in atmospheric processes, nor do they consider uncertainty arising from the carbon and sulphur cycle, as well as uncertainty stemming from ocean physics. Sexton and Murphy, (2010) provides three examples where the 11SCP should be used in place of the 10,000 sample ensemble; (1) the user needs to investigate how two or more variables vary together where different simulations are concerned, for example when the climate change impact is calculated using the difference between north and south summer rainfall; (2) The user is undertaking a nationwide assessment in which locations cannot be treated separately; (3) The user requires climate variables which are located in different batches of UKCP09 for an impact model. Sexton and Murphy, (2010) also provide two examples, which on first glance appear to require spatially coherent projections, but in reality do not. (1) The user wants to create maps identifying impacts associated with a specified probability level from the sampled data. This course of action did not necessarily require the data to be spatially coherent, for example the 9,000th ranked projection (equivalent to 90% “probability” level) can be extracted for each grid square and the results then aggregated to produce the desired map. (2) The user wants to create a map showing the heaviest rainfall at each grid square using the UKCP09 WG, in reality the user only needs to know the values of the driving variables in each grid square and does not need to consider the values in the other grid squares to be spatially coherent.

5.2.5 Sub-sampling UKCP09

One of the key challenges facing users of UKCP09 is the sheer number of climate change projections that are provided. UKCIP recommends decision makers use a minimum of 100 climate change projections in order to preserve the probabilistic characteristics of the underlying projections (Christierson et al., 2012). Of course

a sample this large may still be beyond the capabilities of many complex models, in particularly national scale models (Christierson et al., 2012) and computationally demanding models such as DSSAT (Daccache et al., 2011). As a result, it is often necessary to sub-sample the 10,000 sample ensemble, alternatively, a rapid assessment model can be used though these are discussed elsewhere and in greater detail, see Haasnoot et al., (2012) and Kwakkel et al., (2012). The design and complexity of these sampling methods will depend on both the availability of resources and technical expertise to the decision maker in question.

The size of these sub-samples and choice of sampling methodology are particularly important. Basing decisions on a single or small subset of projections can result in maladaptation, if events occur which are outside the range described by that subset of projections. Using a wide range of projections can lead to increased adaptive capacity, although it is not guaranteed to be more successful, especially if the “real” future climate is not expressed by any single projection within the available projections (Dessai and Hulme, 2007). Furthermore, if the potential climate change impacts are diverse and the projections too numerous or difficult to interpret, the identification of suitable adaptation measures may become too complex and no action may be taken, with potentially serious consequences.

Latin hypercube sampling (LHS) (McKay et al., 1979) has previously been shown to be an effective tool for sub-sampling the UKCP09 dataset (Christierson et al., 2012). In two dimensions, a Latin hypercube can be represented by a simple grid, with one climate variable represented by a row and the other climate variable a column. A Latin hypercube with more dimensions can be considered the generalisation of this concept. This study utilises two types of Latin hypercube sampling, specifically optimum and Maximin. Optimum LHS uses a columnwise-pairwise algorithm to generate an optimal design using an S optimality criterion (Liefvendahl and Stocki, 2006). An S optimality criterion seeks to maximise the average distance between design points or projections to all other points in the state space (Stocki, 2005). In contrast, Maximin LHS maximizes the minimum

distance between design points, this ensures the points out are spread out across the state space (Stein, 1987).

Results of this chapter are presented from the perspective of a decision maker would typically use Laplace, in line with emerging documentation in the field of environmental management, see for example Environment Agency, (2013), though the decision outcomes obtained using other decision criteria (i.e. Maximin, Maximin, Minimax regret and Hurwicz's criterion) are presented for completeness, a more in-depth discussion of these other decision criteria can be found in CHAPTER 7.

5.3 Objectives

The purpose of this chapter was to examine the implications of different ways of using probabilistic climate change projections and explore the impact of uncertainty on decision making, using a case study of irrigation reservoir and SUDS design at three sites in the UK on the basis of the 2050s low, medium and high emission scenarios. The objectives are of this chapter are thus; 1) critically compare the 11SCP and the 10,000 sample ensemble datasets. Establish whether these datasets would yield different decision outcomes and explore the implications of using probabilistic projections in place of non-probabilistic (deterministic) projections. 2) Establish whether sub-sampling the probabilistic projections is appropriate, establish whether different decision outcomes would arise if sub samples were used in place of the complete dataset and explore the implications of using advanced stratified sampling methods (LHS) over simple random sampling methods.

5.4 Methodology

A series of irrigation reservoirs and SUDS were designed using projections derived from the UKCP09 low, medium and high emission scenarios for the 2050s for three sites in the UK. Design reservoir and SUDS capacities were identified using Laplace, Maximin, Maximax, Minimax regret and Hurwicz's criterion using the complete probabilistic dataset (i.e. all 10,000 projections),

11SCP and various sub-samples of the complete probabilistic dataset using different sampling techniques.

Readers are directed to CHAPTER 4 for a detailed description of the methods used to generate the future climate projections used in this chapter.

Irrigation reservoir and SUDS capacities was calculated using each of the 10,000 x 30 year sequences for each site and emission scenario. The median, mean, quartiles and extreme irrigation reservoir and SUDS capacities for each site, emission scenario and dataset were identified and plotted. In order to calculate the optimum irrigation reservoir and SUDS capacity, typical costs and benefits for irrigation reservoirs and a selection of SUDS and traditional drainage devices were obtained using the costs and benefits outlined in CHAPTER 4.

Laplace and the other decision criteria were then used to select the optimum irrigation reservoir and SUDS capacities using all 10000 probabilistic projections (i.e. S1 to S10000), as shown in Table 5.3. For example, for Laplace this was the capacity providing the maximum NPV averaged across the entire 10,000 sample ensemble, whereas for Maximin this was the capacity providing the maximum NPV based on the worst case of the entire 10,000 sample ensemble. Where the result was found to be negative, the capacity was set at zero i.e. it was assumed no reservoir would be built.

Table 5.3 Simplified example of calculations using the decision criteria and median “optimum” option representing the irrigation reservoir and SUDS capacity (not actual data)

Option (reservoir/SUDS capacity)	State				Outcome/Decision criteria				
	S1	S2	S3	etc.	Average (<i>Laplace</i>)	Minimum (<i>Maximin</i>)	Maximum (<i>Maximax</i>)	Minimum regret (<i>Minimax regret</i>)	Weighted average (<i>Hurwicz</i>)
A	10	20	50	100	45	10	100	900	55
B	2	3	3	1000	252✓	2	1000✓	199✓	501✓
C	200	200	202	202	201	200✓	202	798	201
D	100	110	120	410	185	100	410	590	255
etc.									
Largest NPV	200	200	202	1000	Decision criterion outcome (✓)				
“Optimum” option	C	C	C	B	B	C	B	B	B
Median option			C						

The whole process was then repeated for the 11SCP dataset and the results compared, a schematic diagram of the steps taken to generate the future series and the comparisons made is shown in Figure 5.1 (irrigation reservoir case study shown).

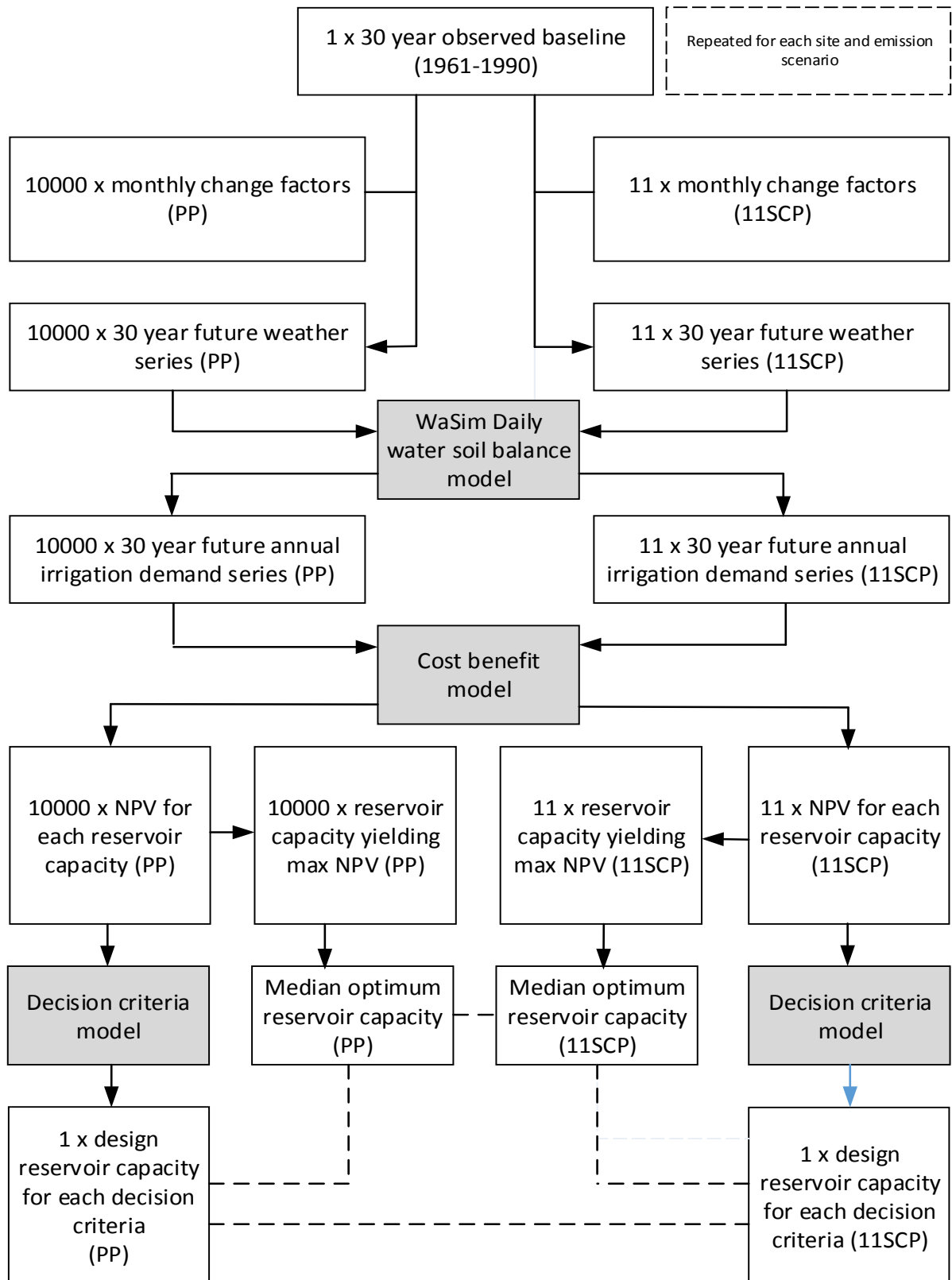


Figure 5.1 Methodology schematic flow chart (dotted line shows comparison made)

To examine the implications of different ways of using probabilistic climate change projections and explore the impact of uncertainty on decision making associated with moving from a single deterministic projection to probabilistic projections, it is of course necessary to know the single projection that would have been used if only one projection was provided. However, in the case of UKCP09 sample ensemble, no such single “most-likely” projection exists when dealing with multiple climate variables; each of the 10,000 probabilistic projections is considered to be equally likely (UK Climate Impacts Programme, 2014). It would be tempting, but potentially misleading, to try to select one with median temperature, median rainfall, etc.; however, such a combination could actually be unlikely. Selecting the most-likely projection within a single variable would require a partly arbitrary choice; using a different variable would probably lead to a different projection.

A comparison against the state (i.e. projection) with the “most likely decision outcome” or median decision outcome was used here, though of course identifying that state required all the projections to be modelled first. The reservoir and SUDS capacity providing the maximum NPV was identified for each projection and the median value i.e. the capacities which has an equal probability of being exceeded and not being exceeded across all 10,000 scenarios selected. However it is important to stress that the projection underpinning this median optimum outcome or reservoir and SUDS capacity is not necessarily the median climate projection; in a non-linear system using the average or median values of the individual climate parameters does not necessarily give the average or median impact.

The differences in irrigation reservoir and SUDS capacities between using all of the probabilistic projections and all of the 11SCP, using Laplace and other decision criteria, and the median optimum irrigation reservoir and SUDS capacities were then assessed. This chapter distinguishes between two sources of uncertainty; (1) uncertainty attributed to differences between the 11SCP and 10,000 sample ensemble and (2) emission scenario uncertainty. The chosen methodology enabled both sources of uncertainty to be simultaneously compared

whilst providing an insight into the impact of uncertainty to decision making for irrigation reservoir and SUDS design. Uncertainty associated with the 11SCP and 10,000 sample ensemble was assessed by comparing differences between the median optimum irrigation reservoir and SUDS capacities i.e. the “most likely” outcomes and the range of outcomes of both datasets represented by box and whisker plots. The impact of emission scenario uncertainty was assessed by comparing the differences in irrigation reservoir and SUDS capacities between the low, medium and high emission scenarios. The impact of the choice of decision criteria was also assessed by comparing the irrigation reservoir and SUDS capacities based on different decision criteria with the median optimum reservoir and SUDS capacity representing the “most likely” outcome.

In order to compare the success of alternative sampling methods, simple random sampling and two variants of Latin hypercube sampling (LHS), optimum and Maximin respectively, were used to sub-sample the probabilistic dataset. Sub-samples created using these methods were compared to each other and the complete dataset in terms of the design irrigation reservoir and SUDS capacities based on Laplace and the other decision criteria. The Latin hypercube method presented here sampled 30 future projections from the 10,000 sample ensemble for the 2050s using six dimensions to stratify the probabilistic dataset for the irrigation reservoir case study and three dimensions for the SUDS case study. For the irrigation reservoir case study these six dimensions consisted of the monthly precipitation and evapotranspiration change factors for June, July and August, representing the three main irrigation months. For the SUDS case study, these three dimensions consisted of the monthly precipitation for November, December and January (representing intense winter precipitation). For both case studies, these dimensions were tested for inter-correlation prior to undertaking LHS. Thirty climate projections were used, as this provided a balance between sampling accuracy and efficiency and was considered to be representative of real world practice (Christierson et al., 2012). Each 30 projection LHS was then compared to the complete dataset as well as the simple random sample (also consisting of 30 projections) by identifying the design irrigation reservoir and SUDS capacity using each of the decision criteria. Each of the projections within

the simple random sample was randomly selected using a random number generator using only the projection number.

5.5 Results

The design irrigation reservoir and SUDS capacities calculated across the 10,000 sample ensemble and across the 11SCP were compared first, using each of the decision criteria in turn. Firstly, design irrigation reservoir capacities using Laplace summarised in Table 5.4 show small differences, generally <5%, between the emission scenarios, but generally larger differences between using the probabilistic projections and 11SCP 0 to 30%, depending on the site and emission scenario). Furthermore, design SUDS capacities using Laplace summarised in Table 5.4 show small differences, generally <10%, between the emission scenarios, but generally larger and highly variable differences between using the probabilistic projections and 11SCP 0 to 20%, depending on the site and emission scenario. Based on design irrigation reservoir capacity, the largest differences between the probabilistic projections and the 11SCP were recorded at Woburn based on the low 22%, medium 26% and high 26% emission scenarios. Similarly large differences in design SUDS capacities were recorded at Woburn based on the low 16%, medium 15% and high 20% emission scenarios. These results suggest that the additional uncertainty considered by the probabilistic projections (and that is absent from the 11SCP) has a much larger impact on irrigation reservoir and SUDS design compared to the choice of emission scenario, though this result is dependent to some extent on the site in question and emission scenario used. For example, using Laplace to design irrigation reservoirs at the site of Slaidburn resulted in no action been taken for all three emission scenarios, as the average NPV of the irrigation reservoir capacities considered was negative, thus no-action was considered preferential. This result on part agrees with Harris et al (2013) who found that the choice of emission scenarios had a comparable small impact on future water shortages in the public water supply sector. In addition, the results show that using the probabilistic projections consistently resulted in building a bigger irrigation reservoir compared to using the 11SCP, regardless of the site and emission

scenario used. In contrast, a previous study by Kay and Jones (2012) found that the median of the probabilistic projections and 11SCP were generally in agreement regarding changes in flood frequency. Similar results were obtained using the other decision criteria, with the exception of Maximin, which suggested not building an irrigation reservoir when using the probabilistic projections.

Table 5.4 Design irrigation (mm) reservoir and SUDS capacities (m³) calculated using Laplace across the entire 10,000 sample ensemble (PP) versus the 11SCPs, for Brooms Barn, Slaidburn and Woburn, for the 2050s low, medium and high emission scenario.

Case study	Site	Brooms barn			Slaidburn			Woburn		
	Emission	L	M	H	L	M	H	L	M	H
Irrigation reservoir	PP	390	410	400	0	0	0	360	380	390
	11SCP	350	350	360	0	0	0	280	280	290
SUDS	PP	2500	2450	2500	4600	4750	4850	2450	2400	2550
	11SCP	2150	2450	2500	4550	4600	4750	2050	2050	2050

The ranges of irrigation reservoir and SUDS capacities, providing the maximum NPV for each of the projections for each dataset were then compared. Box and whisker plots showing the min, Q1 (25th percentile), median, Q3 (75th percentile) and max reservoir and SUDS capacities for all three sites are shown in Figure 5.2. In the case of irrigation reservoir design, the probabilistic projections produced a much wider interquartile range compared to the 11SCP, and at Brooms Barn and Woburn the median optimum irrigation reservoir capacities were larger compared to the 11SCP. On the basis of SUDS design, the interquartile range of the probabilistic projections and 11SCP were similar, however the probabilistic projections tended to have a wider range when the maximum and minimum projections were included. In terms of median optimum SUDS capacity, both datasets identified similar capacities. These results, consistent with the previous findings, suggest that the choice of dataset and the range of uncertainty it considers has a much larger impact on the decision outcome compared to the choice of emission scenario.

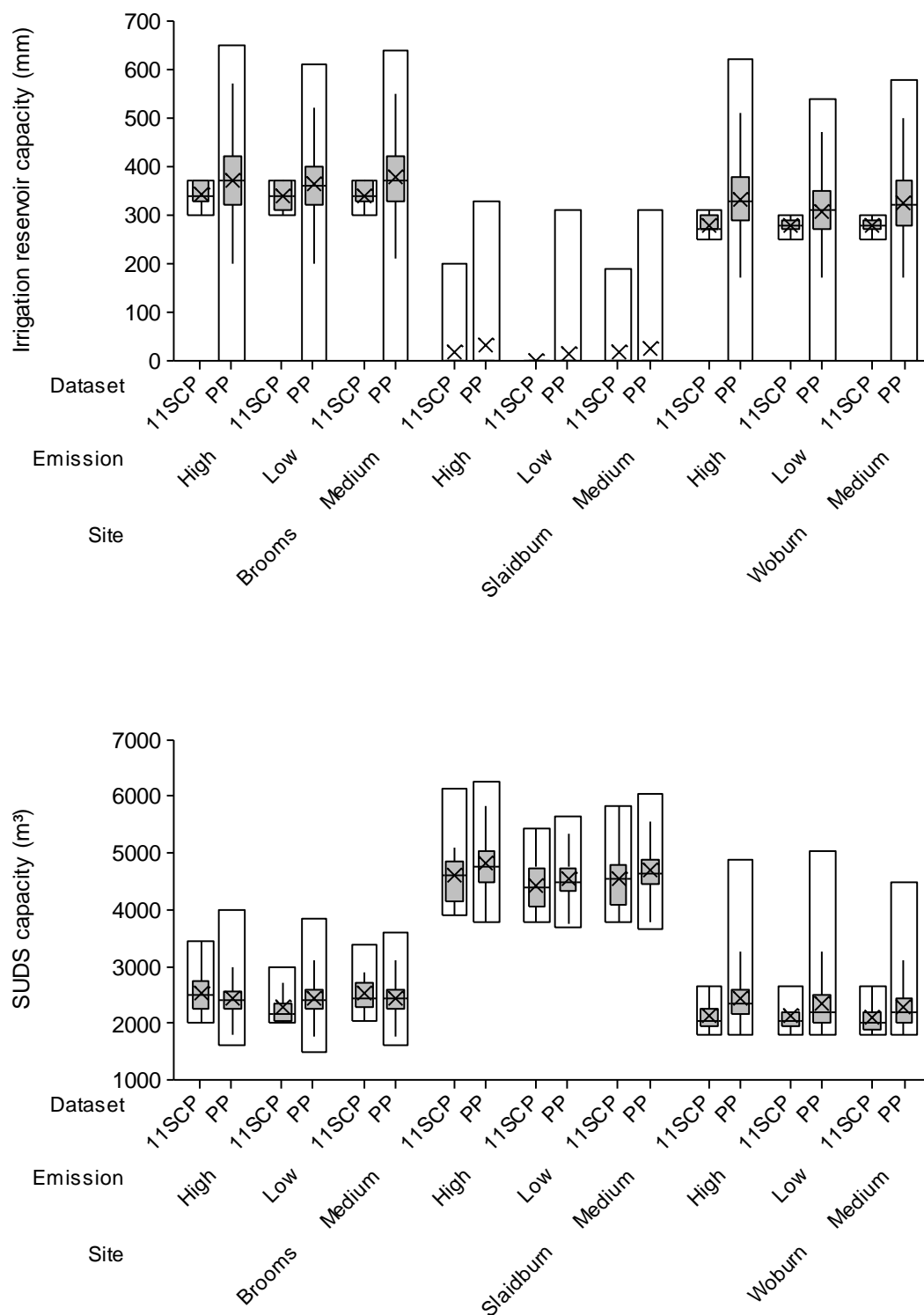


Figure 5.2 Median optimum irrigation reservoir (mm) (above) and SUDS (m³) (below) capacities using each of the 10,000 sample ensemble and each of the 11SCP projections individually, for Brooms Barns. Plots show minimum, Q1 (25th

percentile), median, mean (X), Q3 (75th percentile) and maximum optimum irrigation reservoir and SUDS capacity for each dataset. Upper error bar calculated using $Q3 + 1.5 (Q3-Q1)$, lower error bar calculated using $Q1 - 1.5 (Q3-Q1)$

Next, the median optimum capacities of both datasets, representing the “most-likely” decision outcomes, were compared to the design irrigation reservoir and SUDS capacities on the basis of each decision criteria across all of the probabilistic projections and across all of the 11SCP (Table 5.5).

Table 5.5 Irrigation reservoir capacities (mm) calculated using median “most likely” decision outcome and compared to the design reservoir capacities calculated using Laplace and other decision criteria using the complete probabilistic dataset (PP) and 11SCP for all three sites. Hurwicz’s criterion calculated using coefficient of optimism $\alpha=0.5$.

Decision criteria	Site	Brooms barn			Slaidburn			Woburn		
	Emission	L	M	H	L	M	H	L	M	H
Median optimum reservoir capacity	PP	360	370	370	0	0	0	310	320	330
	11SCP	340	340	340	0	0	0	280	280	270
Laplace	PP	390	410	400	0	0	0	360	380	390
	11SCP	350	350	360	0	0	0	280	280	290
Maximin	PP	0	0	0	0	0	0	0	0	0
	11SCP	300	300	300	0	0	0	250	250	250
Maximax	PP	600	620	650	280	310	330	530	580	620
	11SCP	370	370	370	0	190	200	300	300	310
Minimax regret	PP	420	450	430	100	120	140	380	420	440
	11SCP	350	350	350	0	0	0	280	280	290
Hurwicz	PP	560	590	600	270	300	300	510	540	570
	11SCP	370	370	370	0	0	0	290	280	290

Table 5.6 SUDS capacities (m³) calculated using median “most likely” decision outcome and compared to the design reservoir capacities calculated using Laplace and other decision criteria using the complete probabilistic dataset (PP) and 11SCP for all three sites. Hurwicz’s criterion calculated using coefficient of optimism $\alpha=0.5$.

Decision criteria	Site	Brooms barn			Slaidburn			Woburn		
	Emission	L	M	H	L	M	H	L	M	H
Median optimum SUDS capacity	PP	2400	2450	2400	4500	4650	4750	2200	2200	2350
	11SCP	2150	2450	2500	4400	4550	4600	2050	2000	2050
Laplace	PP	2500	2450	2500	4600	4750	4850	2450	2400	2550
	11SCP	2150	2450	2500	4550	4600	4750	2050	2050	2050
Maximin	PP	1500	1900	1600	3950	3950	3800	1800	1800	1800
	11SCP	2150	2500	2550	3800	3800	3900	1800	1800	1800
Maximax	PP	3800	3600	4000	5550	5400	6250	5050	4500	4800
	11SCP	3000	3400	3450	5450	5850	6150	2200	2150	2200
Minimax regret	PP	2750	2550	2900	4800	5000	5300	3600	3350	3650
	11SCP	2500	2800	2850	4900	5200	5450	2000	2000	2000
Hurwicz	PP	3050	2850	3100	5000	5100	5700	4600	4450	4750
	11SCP	2150	2900	2800	5350	5700	6000	2050	2100	2050

It is evident (Table 5.5 and Table 5.6) that decision outcomes resulting from an individual who considers themselves risk neutral i.e. someone who would typically use Laplace would not be substantially different regardless of whether a “most likely” projection was used instead of the complete probabilistic dataset or the 11SCP, given the comparably small differences 0-20%, between the irrigation reservoir capacities obtained using Laplace and the median optimum reservoir capacities, similarly small differences generally <10%, were recorded between the SUDS capacities obtained using Laplace and the median SUDS capacities at all the sites investigated. Where irrigation reservoirs and SUDS were indicated, the design capacities using Laplace with the complete dataset were higher than using the median values. In addition, irrigation reservoir capacities using the probabilistic dataset were generally higher than using the 11SCP dataset; similarly SUDS capacities calculated using the probabilistic dataset were

generally higher than using the 11SCP dataset, although exceptions were noted at some sites, emission scenarios and when using certain decision criteria.

In contrast, the differences between datasets when using the other decision criteria were much larger and far more variable. The difference between the probabilistic projections and median optimum irrigation reservoir and SUDS capacities were also generally larger than the difference between the 11SCP and the median optimum reservoir and SUDS capacities. This result can be largely attributed to the wider range of projections and uncertainty considered by the probabilistic projections which differ substantially in their decision outcomes. At Slaidburn, for the irrigation reservoir case study, the low annual irrigation demand typically favoured taking no action meaning the differences between the probabilistic projections and median optimum reservoir capacity tended to be large regardless of the decision criteria or dataset used.

When used with the complete probabilistic dataset certain decision criteria such as Maximax and Maximin resulted in very extreme decision outcomes such as taking no action or building very large irrigation reservoirs and SUDS. Sub-samples of the probabilistic projections were taken and the design irrigation reservoir and SUDS capacities obtained using different decision criteria compared with the results obtained using the complete probabilistic dataset. Decision outcomes from certain decision criteria were successfully reproduced from sub-sampling while others such as Maximin and Maximax were not. The percentage difference between the design irrigation reservoir and SUDS capacities calculated using the complete probabilistic dataset and the average of 30 sub-samples each consisting of 30 projections for each decision criteria are shown in Figure 5.3.

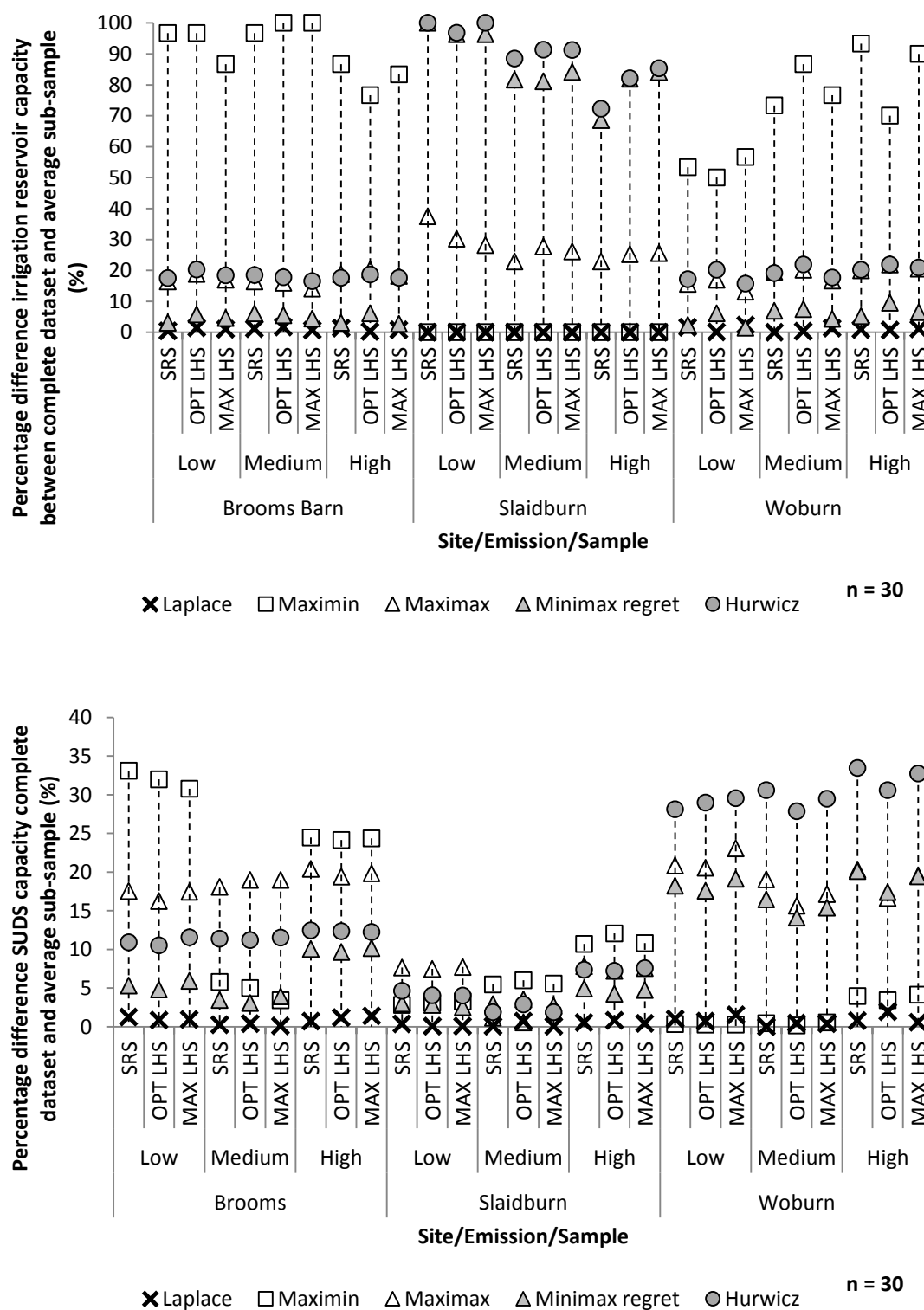


Figure 5.3 Design reservoir capacity (above) and SUDS capacity (below) percentage differences using various decision criteria at Brooms Barn, Slaidburn and Woburn and different emission scenarios with selected sampling methods. Percentage difference represents the difference in design reservoir and SUDS

capacity using the complete dataset and the average of 30 sub-samples (each consisting of 30 projections). Hurwicz's criterion calculated using coefficient of optimism $\alpha=0.5$.

Simple random sampling, optimum LHS and Maximin LHS performed comparably. Christerson et al., (2012) previously suggested that LHS is an appropriate sampling approach for use with the probabilistic dataset. However, on the basis of these results it did not noticeably improve the “reproducibility” of the design irrigation reservoir and SUDS capacities from the sub-samples i.e. the percentage differences between the sub-samples and the complete probabilistic dataset did not vary greatly between sampling methods. All three sampling approaches had similar reproducibility, regardless of the decision criteria and site used. The number of projections contained within each sample i.e. 30 was purposely designed to be representative of real-world practice; further work using much larger sample sizes is recommended, although whether this would be representative of practical real-world application is open to debate.

Sub-sampling highlighted the shortcomings of some of the decision criteria. Design irrigation reservoir capacities calculated using Maximin, Maximax and Hurwicz's criterion were poorly reproduced from sub-sampling (Figure 5.3). Similarly, Minimax regret was poorly reproduced at Slaidburn, however at Brooms Barn and Woburn the design irrigation reservoir capacity was reproduced reasonably well from sub-sampling, evident from the small percentage differences (Figure 5.3). The decision outcome associated with Laplace, consistent with previous findings, was reproduced well from sub-sampling. In addition, unlike the other decision criteria, the difference between Laplace's design irrigation reservoir capacities calculated using the complete probabilistic dataset and sub-samples was not affected by the site or emission scenario. In contrast, design SUDS capacities at Brooms Barn and Woburn calculated using Maximax, Hurwicz's criterion and to a lesser extent Minimax regret, when compared to the other decision criteria, were poorly reproduced from sub-sampling (Figure 5.3). At Slaidburn, design SUD capacities calculated using all of the decision criteria were reproduced exceptionally well from sub-sampling, evident from the similar and small percentage differences (Figure 5.3). At Woburn

and to a lesser extent Brooms Barn, design irrigation reservoir capacities, calculated using Maximin were reproduced equally from well sub-sampling. On the basis of both case studies, decision outcomes obtained using Laplace, consistent with previous findings, were reproduced exceptionally well from sub-sampling. In addition, unlike the other decision criteria considered here, the difference between the decision outcomes obtained using Laplace in combination with the complete probabilistic dataset and sub-samples was not affected by the site nor emission scenario. Comparing the two case studies, the percentage difference between the design irrigation reservoirs obtained using the complete dataset and from sub-sampling were with the exception of capacities calculated using Laplace and Minimax regret consistently larger than the percentage difference between the design SUDS capacities obtained using the complete dataset and sub-samples. This result would suggest that using sub-samples of the complete probabilistic dataset for the purpose of designing irrigation reservoirs may have much larger implications for decision making when compared with SUDS design, whether the same is true for other asset design is a recommended area for further work.

5.6 Discussion

Climate change uncertainty abounds as a result of epistemic and aleatory uncertainty. Uncertainties stemming from a lack of knowledge e.g. cloud physics, randomness e.g. chaotic nature of the climate system and the result of future anthropogenic activity, whose effects may be far reaching and span many decades, but which are very much uncertain e.g. GHG emissions, economic development, population growth etc. (Dessai et al., 2009). It is long been argued that effective adaptation necessitates an understanding of the uncertainty and is dependent on the availability of and access to accurate and precise climate change information (Cooper, 1977; Kelly, 1979; Hickox and Nichols, 2003; Murphy et al., 2004). Partial quantification of uncertainty has been attempted in recent years, although is an area of continual debate and development (Stainforth et al., 2005; Rougier, 2007; Tebaldi and Knutti, 2007).

Despite the seemingly irreducible uncertainty, decision makers still need to, and regularly do, make decisions without having access to accurate predictions. Various criteria and methods are available to assist them in doing so, the majority of which provide justifiable results in the absence of accurate and precise projections (Dessai et al., 2009; Polasky et al., 2011). These criteria and methods typically work by identifying strategies that perform reasonably well over a wide range of future states at the expense of some loss of optimum performance.

It has previously been suggested that current decision criteria are applicable to adaptation planning (Dessai et al., 2009; Ranger et al., 2010; Polasky et al., 2011). At the time of writing, climate change impact assessments using UKCP09 are beginning to emerge, particularly within the building sector (Hanby and Smith, 2012; Williams et al., 2012). Despite growing awareness on the need for adaptation, practical examples of adaptation using current decision criteria appear lacking despite receiving renewed attention in recent years (Polasky et al., 2011).

Certain decision criteria are calculated using a single projection; it is these methods that were generally poorly reproduced from sub-samples of the complete probabilistic dataset. Given the sensitive nature of the design irrigation reservoir and SUDS capacities to extreme projections it is not surprising that some sampling approaches appear inadequate when used in combination with these decision criteria. This result should serve as a warning for users of certain decision criteria with sub-samples of the probabilistic dataset as opposed to a reason for inaction. None of the sampling approaches considered here, performed ideally. However, the alternative would require each of 10,000 sample ensemble to be modelled and the sampling strategy constructed in such a way as to ensure reasonable coverage of the samples across the state space. Unfortunately, such an approach is rarely feasible in practice due to the non-linear nature of climate variables and impacts and the complex nature and potentially long run times of models capable of simulating hydrological processes (Christierson et al., 2012).

5.7 Conclusion

The results of this chapter showed variable differences between the 11SCP and the 10,000 sample ensemble depending on the decision criteria and projection used to evaluate options. This result was attributed to differences between the 11SCP and the 10,000 sample ensemble, specifically the additional uncertainty considered by the latter. The interquartile and complete range of optimum outcomes suggested by the probabilistic projections were much larger compared to the 11SCP, though the difference between the median optimum reservoir capacity using the 11SCP and probabilistic projections was comparably small compared to the difference between the maximum and minimum irrigation reservoir and SUDS capacities respectively.

In addition, this study recorded variable differences between the probabilistic projections and 11SCP design reservoir and SUDS capacities using different decision criteria and the median optimum reservoir and SUDS capacity, considered here to be the “most likely” decision outcome. Design reservoir capacities calculated using certain decision criteria were more closely related to the median optimum reservoir capacity, specifically Laplace and to a lesser extent Minimax regret. Though it should be stressed that use of a single “most likely” projection in the manner described here should be avoided. Probabilistic projections present their own challenges and some of the current decision criteria are not ideal. However despite associated challenges, they remain popular because they are simple to implement and are founded on rational models which can be reasonably justified.

With regards to the sources of uncertainty addressed in this chapter, the results would suggest that the source of uncertainty that had the greatest impact on irrigation reservoir and SUDS design is the dataset used to evaluate options. Prior to the release of UKCP09, decision makers are likely to have focussed their attention on emission scenario uncertainty, as this was the source of uncertainty readily communicated to decision makers in the form of different emission scenarios. While differences between emission scenarios did contribute to the decision outcome, their impact was comparably small when compared with

moving from the 11SCP to the 10,000 sample ensemble and the additional uncertainty considered by the latter. These differences were most apparent where the decision maker exhibited a polarised risk appetite, as the extra uncertainty considered by the latter had a much larger impact where the maximum and minimum payoffs were used to compute design irrigation reservoir and SUDS capacities. It is not clear whether the same is true for other assets in the field of water management. However, it is expected that if the economic performance of an asset is very sensitive to its size, then it is very likely that considering additional uncertainty, such as moving from the 11SCP to the 10,000 sample ensemble will have a large impact on the decision outcome, more so if certain decision criteria are used such as Maximin and Maximax. This chapter did not address the impact of other sources of uncertainties including evapotranspiration uncertainty and statistical post-processing uncertainty associated with downscaling projections. The impact of some of these sources of uncertainty has been generally found to contribute less uncertainty than the probabilistic projections themselves (Kay and Davies, 2008; Kay et al., 2009; Prudhomme and Davies, 2009).

With regards to sampling, it should be noted that sampling methods are ultimately confined by the available data. For the purpose of this study, as with most real-world applications, sampling is used to characterise the climate parameters using a small number projections to ease impact modelling. Sub-samples of the complete probabilistic dataset can then be fed into impact models to inform the decision outcome. However, in a non-linear system using the average or median values of the individual climate parameters does not necessarily give the average or median impact. The decision outcomes resulting from any sampling method, however complex will likely differ from that using the complete dataset. At which point the decision outcome becomes a function of the choice of sampling method and not the underlying dataset, with obvious implications.

Decision outcomes calculated with certain criteria, specifically Maximin and Maximax could not be reliably reproduced from sub-samples of the probabilistic dataset. This was despite trialling a number of different sampling methods, simple

to complex, including LHS. Latin hypercube sampling has previously been shown to be a suitable method for sub-sampling the UKCP09 probabilistic dataset. However, the results of this chapter found that it did not improve the reproducibility of decision outcomes compared to using simplified sampling methods when small sample sizes were concerned. Maximin and Maximax, and by extension Hurwicz should be strictly avoided when working with small sub-samples of the complete probabilistic dataset given the limitations of existing sampling methods and the highly variable nature of the UKCP09 sample ensemble. Laplace emerged as a viable decision criterion for use with small sub-samples of the probabilistic dataset, showing strong reproducibility from different sampling methods. However, as with any decision criterion, Laplace may not appeal to decision maker's rational model and risk appetite and as a result other decision criteria may be sought such as the novel decision criterion presented in CHAPTER 7.

CHAPTER 6. DOWNSCALING: CHANGE FACTOR (DELTA CHANGE) OR STOCHASTIC (UKCP09 WEATHER GENERATOR)

6.1 Overview

This chapter begins by discussing the merits and limitations of deterministic downscaling in the form of a change factor approach applied to the 10,000 member ensemble versus stochastic downscaling using the UKCP09 WG. The difference between the change factor approach and a stochastic weather generator approach to downscaling climate change projections and their implications for decision making is discussed. Results for two case studies at three UK sites using all three emission scenarios, from change factor downscaling using 10,000 member ensemble (change factor) and stochastic downscaling using the UKCP09 WG are presented and their impact on decision making for local water management are explored.

6.2 Background

6.2.1 Introduction

Deciding the optimum capacity of assets such as irrigation reservoir and SUDS, capable of contending with future climate change and its uncertainty is not so simple. In the case of irrigation reservoir/SUDS design, a sufficiently long daily weather record is essential to adequately gauge the amount of water required/stored. For the baseline period (1961-1990), irrigation demand calculations are often based on the observed record, though this may be substituted with a synthetic series from a weather generator provided it has been suitably calibrated. Similarly, a sufficiently long record of future daily weather data is required to model future irrigation demand under the effects of climate change. Such future weather data can be created by downscaling coarse resolution climate change projections from GCMs. Raw GCM outputs are not designed to model hydrological responses such as runoff, as such downscaling is nearly always deemed necessary. GCM predicted runoff is over-simplified, that is it does not consider the movement of water across grid cells (Xu, 1999). There is clear

disparity between climate and hydrological modelling with regards to the spatial and temporal scales that they are undertaken, as well as GCM accuracy and the hydrological significance of climate variables (Fowler et al., 2007). It is an acknowledged limitation that raw GCM outputs cannot reproduce observed precipitation patterns (Salathé, 2003) and variability (Bürger and Chen, 2005), though significant improvements in our ability to model future precipitation at the local and regional can be achieved using even simple downscaling methods such as the change factor approach or a stochastic weather generator (Wilby et al., 1999).

Two datasets, the UKCP09 sample ensemble and the UKCP09 WG, each the product of a different downscaling technique, are used here to generate future projections at a daily resolution. The former was used in combination with the change factor and the latter is an example of using a stochastic weather generator (Table 6.1).

Table 6.1 Summary of downscaling methods

Dataset	Downscaling method	Sample Size	Description
UKCP09 Sample ensemble	Change factor	10,000	1 x Observed baseline (1961-1990) perturbed using 10,000 sets of monthly change factors (PE changes not available so estimated using Penman-Monteith)
UKCP09 WG	Weather generator	10,000	1 x Synthetic baseline (1961-1990) and one future (2040-2069) set of daily time-series for each Weather Generator run.

6.2.2 Change factor (delta change) downscaling

GCM outputs are often only available as monthly values, which are generally insufficient for modelling dry year supplemental irrigation demand and many hydrological processes (Holman et al., 2009). They can however be used to

perturb an observed or synthetic daily series using the ‘change factor’ approach (Arnell and Reynard, 1996; Boorman and Sefton, 1997; Loaiciga *et al.* 2000; Prudhomme *et al.* 2002). The change factor method remains a popular approach, given its relative simplicity, low computation demands and effectiveness for simulating hydrological systems (Salathé, 2003; Fowler *et al.*, 2007; Daccache *et al.*, 2012). The UKCP09 sample ensemble presently provides the greatest coverage of climate change uncertainty.

It should be noted that the application of the sample ensemble to an observed baseline by means of the change factor approach does not allow for the simulation of climate variability, e.g. the same patterns of wet and dry days will occur in the future dataset as in the original baseline (Kilsby *et al.*, 1998; Harris *et al.*, 2012). Simulation of climate variability typically would require access to time series methods (Kay and Jones, 2012). However, the usefulness of time series methods is dependant to a large extent on the ability of weather generators and climate models to provide meaningful climate inputs. The range of downscaling methods on offer can produce very different results depending on the location and the nature of the system being modelled. The severity and extent of impacts would also depend on the baseline and change factors used, equally model structure and parameter uncertainty may also affect the range of outcomes, although the impact of these sources is believed to be less when compared with climate models themselves (Wilby and Harris, 2006; New *et al.*, 2007; Kay *et al.*, 2009).

6.2.3 Stochastic (UKCP09 weather generator) downscaling

Alternatively, a weather generator such as the UKCP09 WG can be used to generate multiple future time series using perturbed synthetic baselines. The UKCP09 WG is available for grid cells covering a 5 x 5 km area for any location in the UK. The projections themselves are not spatially coherent, but unlike the sample ensemble, multiple grid squares can be selected and the resulting UKCP09 WG projections spatially aggregated up to an area of 1,000km² or a total of 40 squares to produce a single time series. Here a collection of 25 grid squares were selected to produce an area equivalent to a single 25 km² sample ensemble

grid square for the purpose of comparison. Sub-samples of the UKCP09 WG can be requested, using random selection or similarly specified using sample IDs, though only a maximum of 1,000 runs can be generated at once. As a result, in order to capture all 10,000 unique IDs, as was done so here, it was necessary to run the UKCP09 WG 10 times for each site and emission scenario using specified batches of 1000 runs (i.e. 1-1,000, then 1,001-2,000 and so on). The minimum number of UKCP09 WG runs that can be requested is 100; this is to maintain that probabilistic nature of the data. If the UKCP09 WG is rerun, a unique set of UKCP09 WG runs will be returned, unless a unique seed is specified prior in which case the same runs will be produced as was done so here. The UKCP09 WG produces stationary time series for periods between 30 and 100 years, at increments of 10 years (Kay and Jones, 2012). Previous studies suggest that the UKCP09 WG projections show generally higher impacts compared to other methods, this result was attributed to the inability of the UKCP09 WG to produce rainfall time series that are fully representative of catchment-averages, particularly for regions with highly variable topography (Kay and Jones, 2012).

Unlike the conventional change factor approach, online pre-calibrated weather generators such as the UKCP09 WG are not dependant on the user having access to a suitably long observed record nor do they assume that the future climate variability is necessarily stationary, making them an attractive tool for undertaking climate change impact assessments. The change factor approach and UKCP09 WG are examples of statistical downscaling (Wilby et al., 2004; Semenov, 2007). Alternative methods collectively referred to as dynamical downscaling techniques also exist but are not used here (Mearns et al., 2003). An extensive discussion of the merits and weaknesses of different downscaling techniques can be found elsewhere and in greater detail (see for example Prudhomme et al., 2002; Fowler et al., 2007). However a summary table from a wider review of the academic literature, outlining the main advantages and disadvantages of the change factor and weather generator approaches is provided in Table 6.2 followed by a short discussion.

Table 6.2 Advantages and disadvantages of change factor and stochastic weather generator downscaling techniques

Change factor	
Advantage	<p>Provides station-scale projections of future climate change.</p> <p>Local climate change projections are directly related to changes in regional climate model output.</p> <p>Computationally simple to implement and can be rapidly applied.</p> <p>Does not require modelling expertise or access to specialist modelling packages.</p> <p>Allow for climate change impact assessments to be conducted at greater temporal resolution compared to regional climate model (RCM) outputs, this is particularly important for studies with a hydrological component where the sequence of events can have a large impact.</p>
Disadvantage	<p>Dependant on the realism of the climate model producing the CF.</p> <p>Temporal sequencing of wet and dry days remains unchanged and is thus not useful where changes in event frequency and antecedent conditions are important to the impact assessment.</p> <p>CF can only be applied where equivalent observation and GCM data exist, i.e. it becomes less useful where observed data and CF differ substantially in their length.</p> <p>CFs are calculated for specific time slices, as a result the method cannot be used to produce transient local climate change projections.</p> <p>Produces clear step changes in scaling at the monthly interface.</p>
Weather generator	
Advantage	<p>Provides station-scale projections of future climate change</p> <p>Climate projection ensembles permit uncertainty analyses.</p> <p>Provides transient climate change projections at an hourly/daily temporal scale.</p>

	Can be used to support exploration of temporal sequencing of meteorological events
	Can recreate missing or erroneous weather records.
	Allow for climate change impact assessments to be conducted at greater temporal resolution compared to regional climate model (RCM) outputs, this is particularly important for studies with a hydrological component where the sequence of events can have a large impact.
	Single site weather generators such as EARWIG, CRU WG, LARS WG and UKCP09 WG are computationally inexpensive.
	Some WGs e.g. UKCP09WG do not require manual data input, prior knowledge of climate modelling or the need to develop local-scale WG.
	Allows non-specialists end users to use WGs, facilitating more widespread uptake in industry.
Disadvantage	End users may be hamstrung by the lack of a particular climate variable, as in the case of UKCP09WG which lacks wind speed data and thus reduces its effectiveness in many sectors, e.g. transport.
	Some WGs are unable to produce extreme meteorological events and are unable to recreate blocking regimes which can lead to heat waves and droughts and exceptionally cold winters.
	Require long and reliable observed historical data series for calibration.
	Dependant on GCM boundary forcing, as a result can be affected by biases in underlying GCM.
	WGs do not provide spatially coherent projections, i.e. an extreme event at one site will not correspond to any other site, extreme events may occur on different days even though the sites are theoretically subject to the same large scale weather systems.
	The spatial extent of projections is variable, in the case of UKCP09 from 5-10,000km ² , but involves spatially-averaging thus reducing the accuracy.
	WGs are often conditioned for a particular climate; as a result they may not be automatically applicable to other climates, though the extent to which they are useful has not been formally tested.
	Some WGs tend to underestimate inter-annual variability, though approaches have been developed to improve the simulation of variability. For example, the use of a stochastic rainfall model has been known to

improve the simulation of both variables and extremes when compared to the use of a simple Markov method.

Predictor-Output relationships are not always stationary

Choice of predictor variables and transfer function may affect model outputs

Adapted from Wilks and Wilby, 1999; Varis et al., 2004; Diaz-Nieto and Wilby, 2005; Fowler et al., 2007; Jones et al., 2009; Harris et al., 2012.

Weather generators were historically used to recreate missing or erroneous weather records (Wilks and Wilby, 1999). While WGs have been widely available for some time (Matalas, 1967; Richardson, 1981) it is only recently their use has been advocated for conducting climate change impact assessments, particularly those incorporating a hydrological component. The reason for this is their ability to recreate plausible high resolution estimates of climate variables, allowing climate change impact assessments to be conducted at a far greater spatial and temporal resolution compared to GCM outputs as well as the view that their use can support robust climate change adaptation (Groves and Lempert, 2007; Dessai et al., 2009; Lempert and Groves, 2010; Harris et al., 2012). Climate change impact assessments incorporating hydrological components have used a range of climate change projections including dynamically downscaled outputs (Wood et al., 2004; Graham et al., 2007), bias-corrected dynamically downscaled outputs (Wood et al., 2004), multiple regression relationships (Jasper et al., 2004), expanded downscaling (Müller-Wohlfeil et al., 2000), stochastic WGs (Evans and Schreider, 2002) and weather typing and circulation indices (Pilling and Jones, 2002).

WGs are to this day typically assessed on the basis of their ability to reproduce the observed or instrumental record (see (Wood et al., 2004; Min et al., 2011)). However in order to do so, it is necessary to first calibrate the WG for a particular catchment as opposed to using a standard assessment criteria (Fowler et al., 2007). Different downscaling procedures can lead to significantly different hydrological impacts even for the same catchment (Coulibaly et al., 2005; Dibikey and Coulibaly, 2005). In order to adapt WGs for future climate change impact assessment it is necessary to accept that statistical relationships between climate variables in the present and future are consistent. Provided this assumption is upheld, WGs can provide an attractive tool for undertaking climate change impact assessments.

The most commonly used and computationally inexpensive form of WGs are single site WGs such as EARWIG, CRU WG, LARS WG (Semenov, 2007) and now UKCP09 WG. Readers are directed elsewhere for further details of their

computation and use (Maraun et al., 2010). Online WGs concealed behind “science hidden” interfaces such as UKCP09 WG are now widely available, and have in some part contributed to the greater undertaking of high spatial and temporal resolution hydrological assessments, particular within the UK (Holman et al., 2009) allowing for non-specialists to use WG-based techniques and thereby encourage more widespread uptake across the water industry as a whole. However, the science-hidden nature of these particular WG may also hamstring users, owing to the lack of particular climate variables and the inability of third parties to dissect and develop these WGs.

WGs suffer from a number of other known limitations. For example version 1 of the UKCP09 WG was unable to reliably recreate extreme meteorological events, arguably one of those most important components of hydrological assessments. WGs also tend to ignore blocking regimes which can result in exceptionally cold winters, heat waves and droughts (Jones et al., 2009). While a number of the original limitations of version 1 of the UKCP09 WG were largely rectified with the release of version 2 of the UKCP09 WG, it is not possible to fully eliminate all of their limitations on account of the fundamental assumptions underpinning most single site WGs. Like the UKCP09 sample ensemble, commercially available single site WGs such as UKCP09 do not provide spatially coherent projections, projections at one site will not correspond to projections at any other site even though in reality these sites may be subject to the same large pattern weather system (Jones et al., 2009). While WG such as UKCP09 can be continually improved and a number of these limitations reduced, it is important to strike a balance between making potentially costly improvements and actually using a WG to inform real-world decisions (Harris et al., 2012). The benefit of WGs such as UKCP09 WG when compared to the conventional change factor approach are well documented, despite this, real-world cases of adaptation using the UKCP09 WG are limited. However, impact assessments using the UKCP09 WG particular within the building industry are beginning to emerge albeit slowly (Hanby and Smith, 2012).

Studies using and comparing downscaling approaches for hydrological assessments are now relatively common see Herrera-Pantoja and Hiscock, (2008) and Holman et al., (2009). It has previously been suggested that WG and conventional downscaling approaches such as the change factor approach occupy their own particular niche, with coarse resolution techniques providing a “broad brush” high level assessment of vulnerability whereas WG allow for sequencing and persistence of events to be explored in much greater detail, typically once vulnerable water resources have been identified (Diaz-Nieto and Wilby, 2005). A common feature of assessment studies comparing different downscaling approaches is that they tend to focus on comparing temperature (Huth, 1999), precipitation (Wilby and Wigley, 1997) and evapotranspiration, with few investigating multiple variables simultaneously (Dibike and Coulibaly, 2005) and fewer still comparing the impact of different downscaling procedures on decision making for adaptation planning itself, none of which have been undertaken within the irrigation agriculture sector or for the purpose of SUDS design.

6.3 Objective

As a result, the objective of this chapter is thus 1) critically compare the change factor (delta factor) and stochastic (UKCP09 WG) downscaling techniques. Establish whether these downscaling techniques would yield different decision outcomes to each other and explore the implications of using one approach over the other.

6.4 Methodology

As an initial check, a baseline calibration exercise was undertaken to establish whether the UKCP09 WG could reliably reproduce observed, precipitation, evapotranspiration and irrigation demand for the baseline period. With the exception of some extreme events, which are beyond the scope of this analysis, version 1 of the UKCP09 WG was found to be reasonably calibrated at a number of UK sites, three of which were selected for further analysis. Readers are

directed to Green and Weatherhead, (2014a) for further details of the methodology undertaken.

Next, the annual irrigation demand and annual maximum runoff was calculated for each year in the 10,000 x 30 year sequences for each site and emission scenario, using both the change factor and version 2 of the UKCP09 WG datasets using the methods listed in CHAPTER 4. The values within the irrigation demand sequences were then ranked from smallest to largest. For the irrigation demand case study, the irrigation demand during the design dry year, referred to hereafter as 80% dry year irrigation demand was calculated for each of the 10,000 sequences, using the 80% probability of non-exceedance rule, roughly equivalent to the older “fourth driest year in five”, representing a current best-practice approach. For each case study, the median, mean, quartiles and extreme irrigation demand and maximum daily runoff values for each site, emission scenario and dataset were identified and plotted. In order to calculate the optimum irrigation reservoir and SUDS capacity, typical costs and benefits were obtained as outlined in CHAPTER 4, to calculate the NPV of these assets, using an assumed discount rate of 3.5%.

The Mann-Whitney U-test (Mann and Whitney, 1947) was used to establish whether there were significant differences between the 10,000 sample ensemble change factor and UKCP09 WG datasets in terms of the 80% dry year irrigation demands, the annual maximum daily runoff and the optimum reservoir and SUDS capacities. The Mann-Whitney U-test was chosen due to the non-parametric nature of the data even after applying transformations. The Mann-Whitney U-test is commonly used to test the equality of two population medians. It is considered the non-parametric alternative to the 2-sample t-test, it assumes that the populations are independent and have a similar distribution shape. Unlike the 2-sample t-test it does not require the two populations to be normally distributed.

In addition, for the irrigation reservoir case study a sensitivity analysis was undertaken to establish how sensitive the decision outcome was to the choice of discount rate, benefit of the water and earthwork costs. Each parameter was varied in turn, keeping the other parameters fixed, and the median optimum

reservoir capacity identified, calculating the percentage difference before and after varying each parameter. The discount rate was initially fixed at 3.5%, water benefit at £1.56.m⁻³ and earthworks at £1.13m⁻³, and subsequently scaled up and down using a linear coefficient.

6.5 Results

For the irrigation demand case study, the 80% dry year irrigation demands were compared between the change factor and UKCP09 WG sequences for each site and emission scenario (Figure 6.1). The median 80% dry year irrigation demand was similar between the datasets. Both datasets also had a similar interquartile range and min-max range. These results seems to support the assumption that, based on current design standards, the UKCP09 WG was reasonably calibrated with the observed record (Green & Weatherhead 2013) and suggest that using the UKCP09 WG instead of the conventional change factor approach in terms of the 80% dry year irrigation demand, representing a current best-practice approach may not necessarily lead to more robust decision making, because the results, are not too dissimilar.

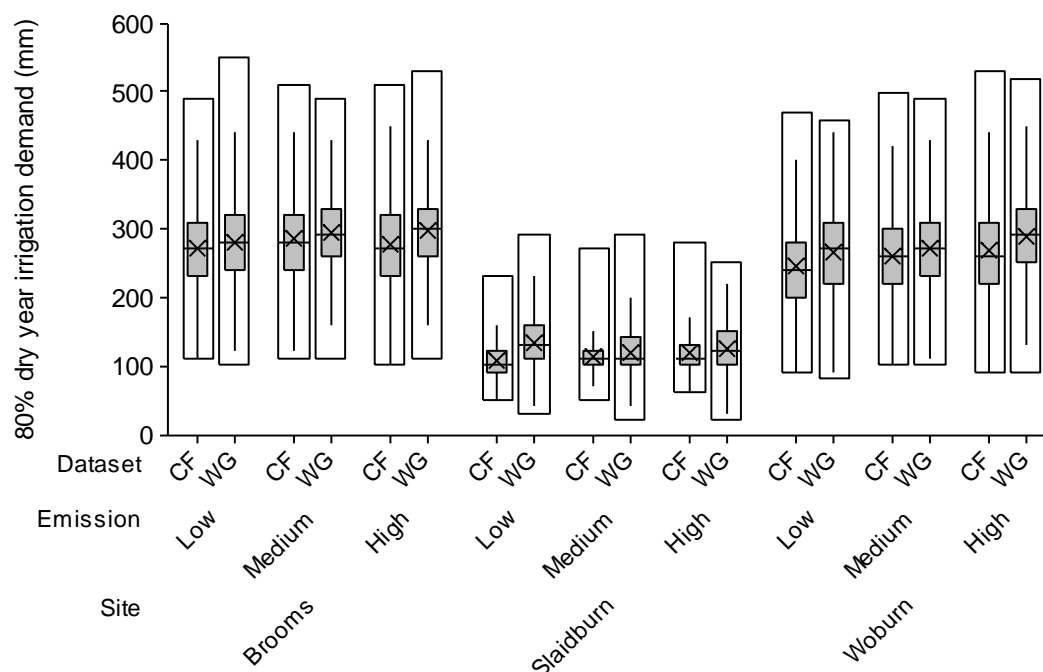


Figure 6.1 Median (-), mean (X), quartile and extreme values of the 80% dry year irrigation demand for the change factor (CF) and UKCP09 WG (WG) sequences for each site and emission scenario (Adapted from Green and Weatherhead, 2014b).

For the urban drainage case study, the maximum daily runoff was compared between using the change factor and UKCP09 WG sequences for each site and emission scenario (Figure 6.2). The median maximum daily runoff was similar across both datasets. Both also had a similar interquartile range, though the UKCP09 WG dataset estimated a slightly wider interquartile range at two of the investigated sites. The min-max range of the change factor and UKCP09 WG datasets on the other hand were noticeably different, with the UKCP09 WG dataset estimating greater runoff compared to the change factor dataset, approximately five times the average estimated runoff. These results do however support the assumption that based on the maximum daily runoff, the UKCP09 WG was reasonably calibrated with the observed record and suggests that using the UKCP09 WG instead of the conventional change factor approach may not necessarily lead to more robust decision making, because the results, excluding some extreme years are again not too dissimilar.

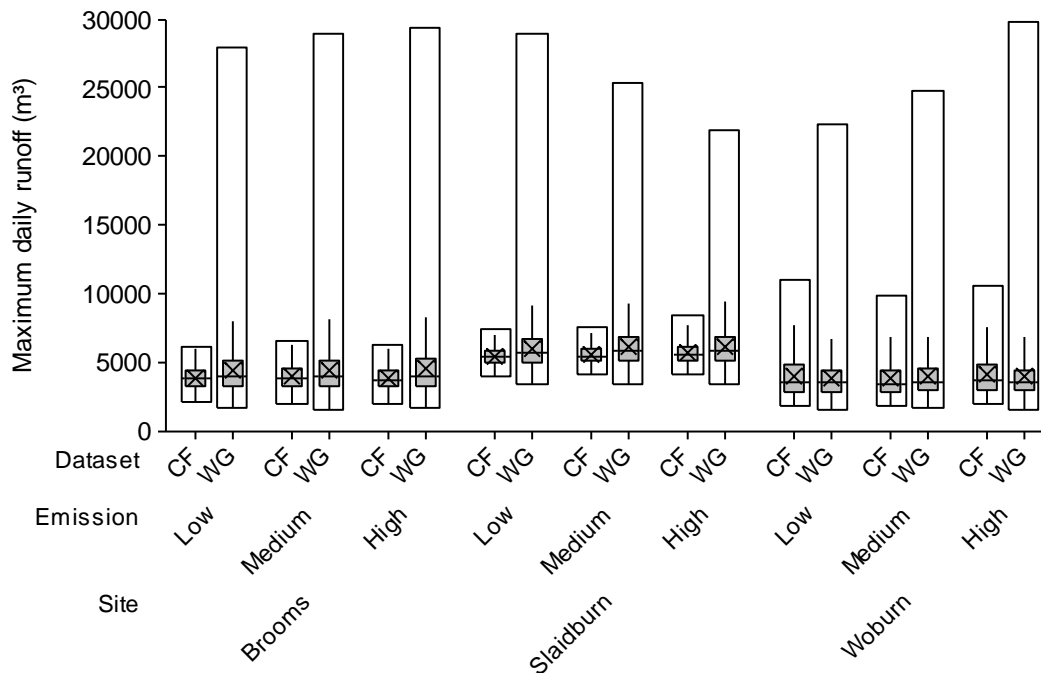


Figure 6.2 Median (-), mean (X), quartile and extreme values of maximum daily runoff for the change factor (CF) and UKCP09 WG (WG) sequences for each site and emission scenario

Next, the economic performance of various irrigation reservoir capacities and SUDS (pond shown) generated using the 10,000 sample ensemble downscaled using the change factor and UKCP09 WG were compared against each other for each site and emission scenario. Similar results were obtained for the other SUDS. Figure 6.3, Figure 6.4 and Figure 6.5 show the results obtained for the sites of Brooms Barn, Slaidburn and Woburn using the medium emission scenario. In the case of the irrigation reservoir case study, despite subtle differences in the projected NPV, both datasets showed a similar trend in NPV against reservoir capacity at the three investigated sites. At Brooms Barn, the UKCP09 WG projected a higher NPV for most reservoir capacities, based on the median projection, with the exception of small reservoirs with a capacity of less than approximately 150 mm. At Slaidburn, the change factor and UKCP09 WG yielded a similar NPV for reservoirs with a capacity of less than 50 mm and at Brooms Barn reservoirs with a capacity of less than 100 mm. At all three sites, the NPV range i.e. the difference between the maximum payoff and minimum

NPV for each reservoir capacity is initially quite narrow and increases with reservoir capacity. In addition, the NPV range is generally larger for the UKCP09 WG dataset than for the change factor dataset for all the reservoir capacities considered. Based on the medium emission scenario using the change factor dataset, at Brooms Barn the median optimum reservoir capacity yielding the largest NPV was 370 mm. In contrast, the UKCP09 WG estimated the median optimum reservoir capacity to be marginally smaller at 330 mm but with a ~15% larger NPV. At Slaidburn the median optimum reservoir capacity based on the medium emission scenario for the change factor dataset was 150 mm. In contrast, the UKCP09 WG estimated the median optimum reservoir capacity to be marginally larger at 160 mm but with a ~35% larger NPV. At Woburn the median optimum reservoir capacity for the medium emission scenario using the change factor dataset was 340 mm. In contrast, the UKCP09 WG estimated the median optimum reservoir capacity to be marginally smaller at 310 mm but with a ~25% larger NPV. While the differences in NPV were considerably different between the change factor and UKCP09 WG datasets, the difference in terms of the action taken i.e. the capacity of reservoir built, was not too dissimilar based on the median projection. This result could be largely attributed to the shallow NPV curves of asset considered at the three investigated sites.

In terms of SUDS capacities, despite subtle differences in the projected NPV, both datasets showed a similar trend in NPV against SUDS capacity at the three investigated sites. At Brooms Barn, the UKCP09 WG projected a higher NPV for most SUDS capacities; based on the median projection and interquartile range, at Slaidburn, the change factor and UKCP09 WG datasets yielded a similar NPV for SUDS with capacity of less than 2,300 m³. At all three sites, the NPV range (i.e. the difference between the maximum payoff and minimum NPV for each SUDS capacity) is initially narrower and increases with SUDS capacity. In addition, the NPV range is generally larger for the UKCP09 WG dataset than for the change factor dataset for all the additional SUDS capacities considered. At Brooms Barn based on the medium emission scenario using the change factor dataset, the median optimum SUDS capacity (yielding the largest NPV) was 2400m³. In contrast, the UKCP09 WG estimated the median optimum SUDS

capacity to be marginally larger at 2,750 m³ but with a ~20% larger NPV. At Slaidburn the median optimum SUDS capacity was 4,700 m³. In contrast, the UKCP09 WG estimated the median optimum SUDS capacity to be smaller at 4,500 m³ with a ~15% smaller NPV. At Woburn the median optimum SUDS capacity was 2,200 m³. In contrast, the UKCP09 WG estimated the median optimum SUDS capacity to be marginally larger at 2,350 m³ but with a negligible difference in NPV. The difference between the change factor and UKCP09 WG datasets in terms of projected NPV was generally large while the difference in terms of the action taken i.e. the capacity of SUDS built, was not too dissimilar based on the median or “most likely” projection. As with the irrigation reservoir case study this result could be largely attributed to the shallow NPV curves of the three investigated sites.

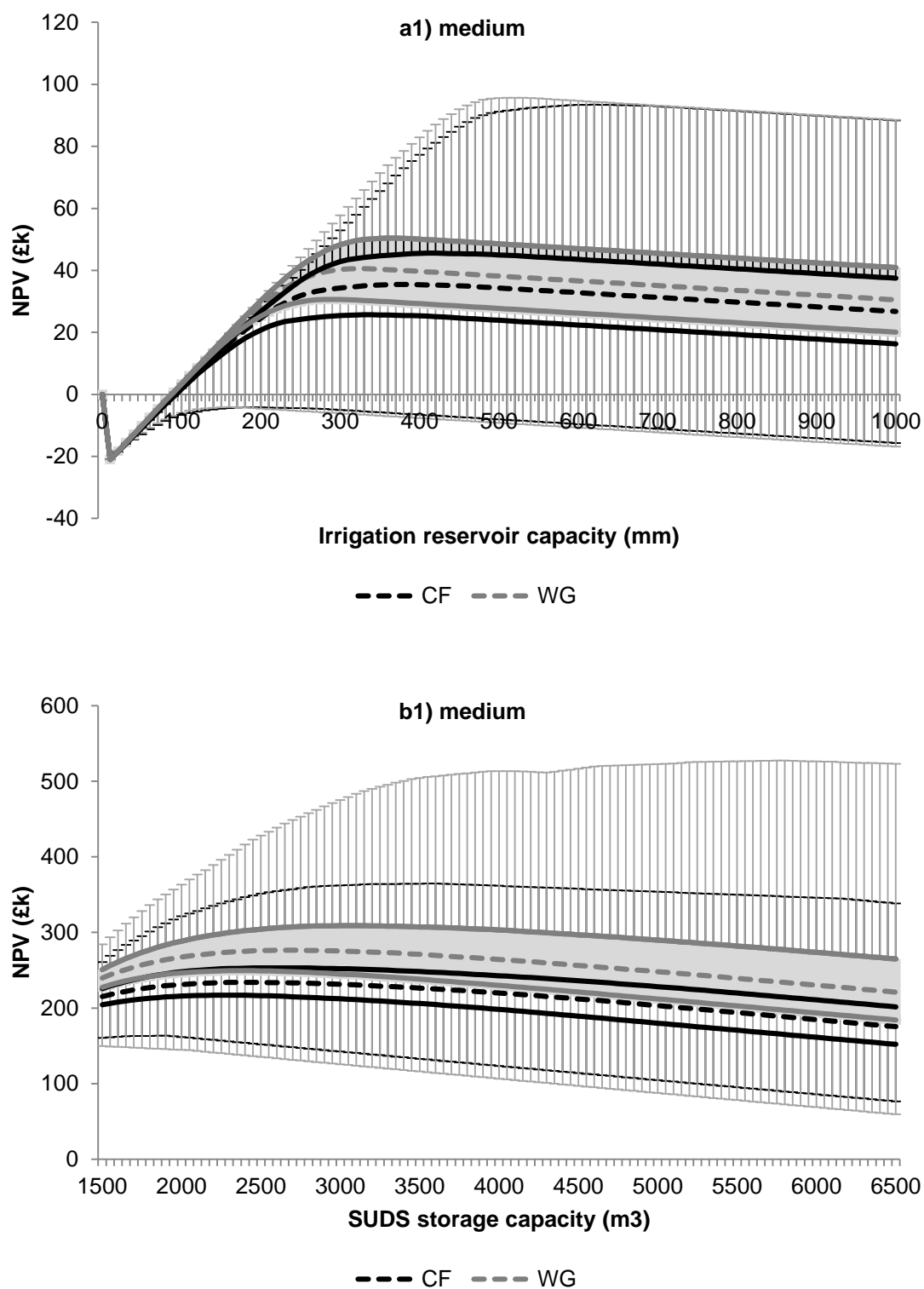


Figure 6.3 Median, quartile and extreme values of NPV against reservoir (a1) and SUDS (b1) capacity for the change factor (CF) and UKCP09 WG (WG) sequences for Brooms Barn medium emission scenario.

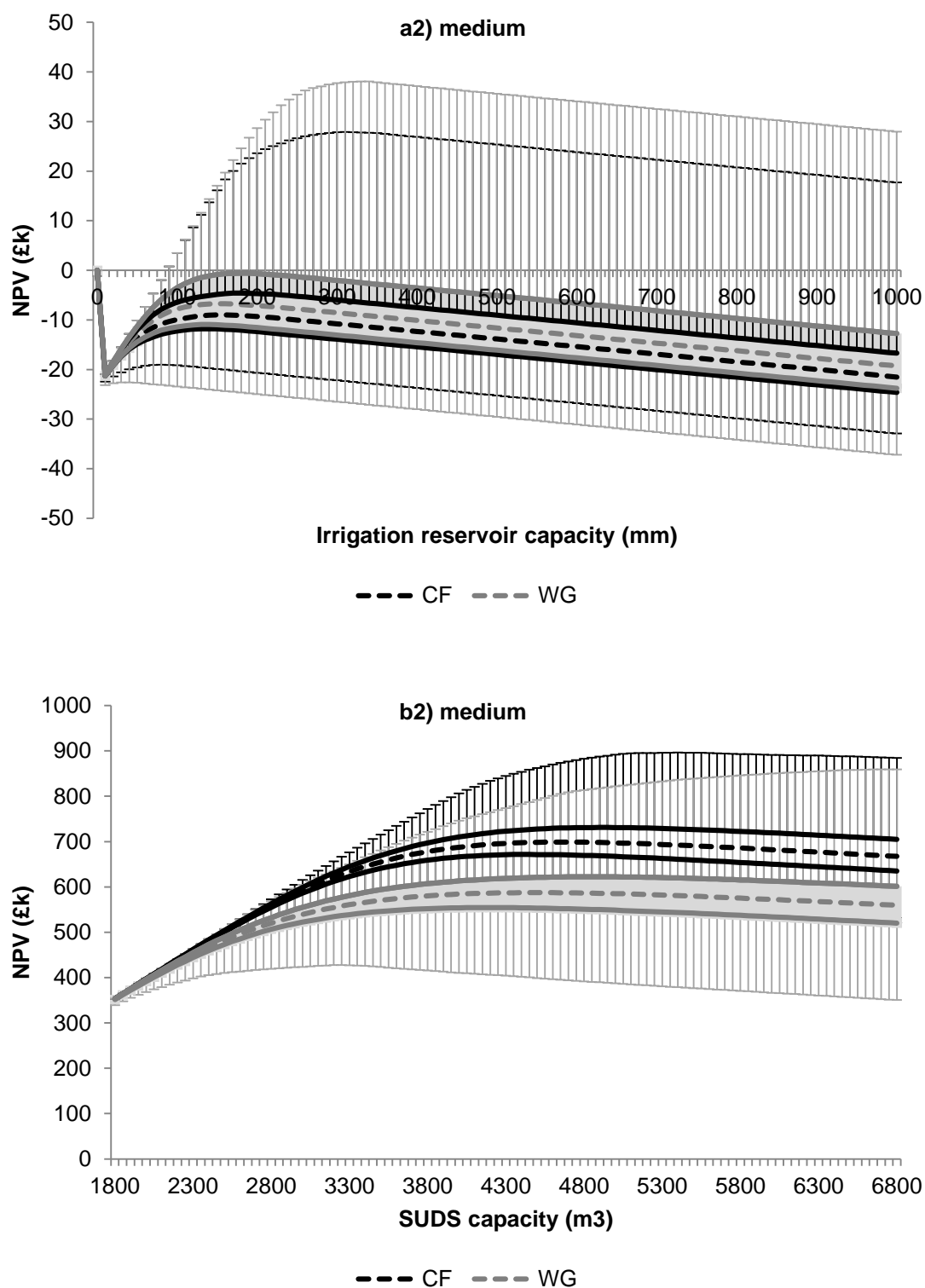


Figure 6.4 Median, quartile and extreme values of NPV against reservoir (a2) and SUDS (b2) capacity for the change factor (CF) and UKCP09 WG (WG) sequences for Slaidburn medium emission scenario.

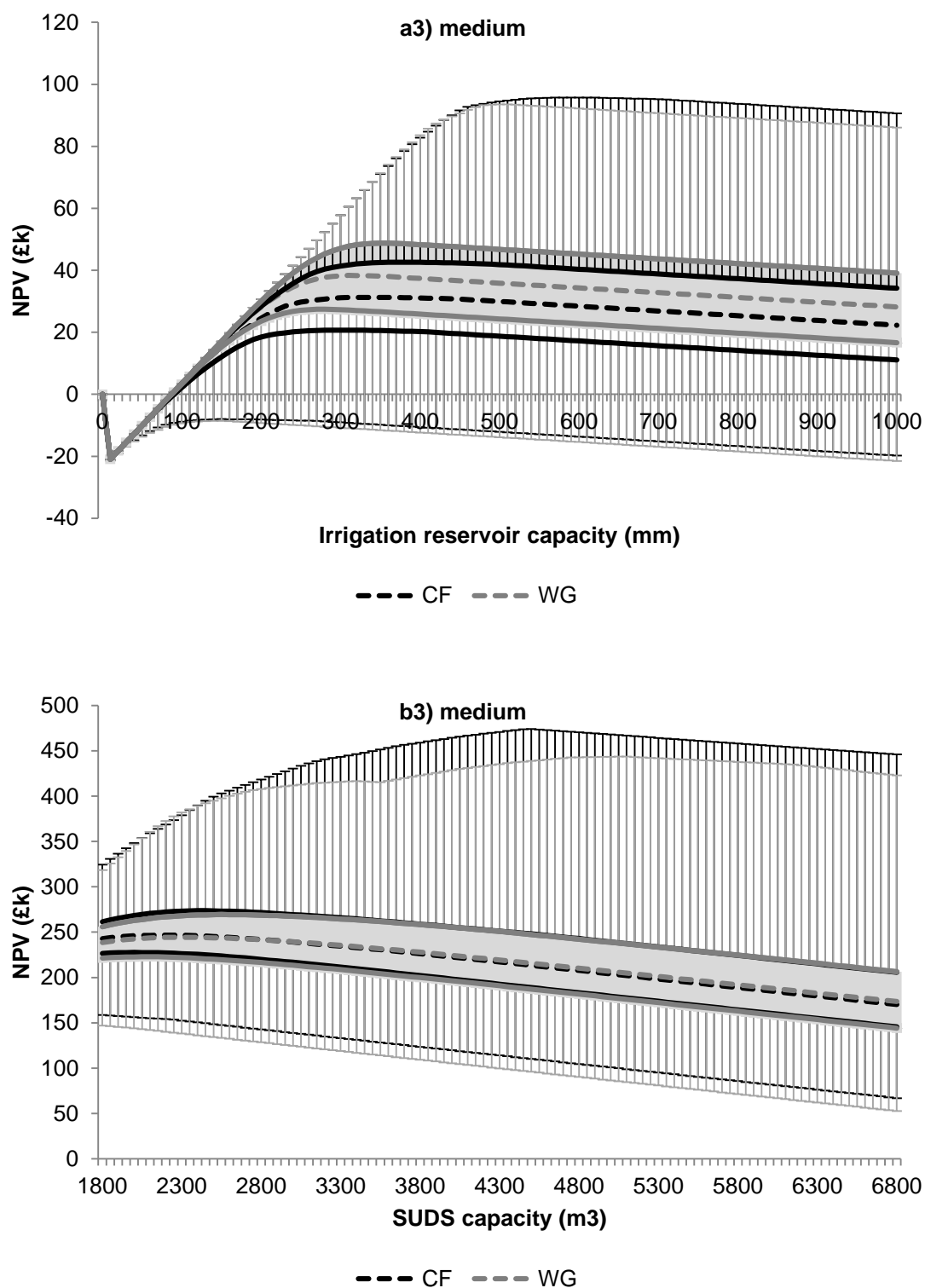


Figure 6.5 Median, quartile and extreme values of NPV against reservoir (a3) and SUDS (b3) capacity for the change factor (CF) and UKCP09 WG (WG) sequences for Woburn medium emission scenario.

Statistical analysis was then undertaken to establish whether there was significant difference between using the change factor and UKCP09 WG datasets in terms of (1) the 80% dry year irrigation demand and (2) the optimum reservoir capacity. The 80% dry year irrigation demand values obtained using the UKCP09 WG dataset were significantly different to those from using the change factor dataset. Similarly, the optimum reservoir capacities calculated using the UKCP09 WG dataset were significantly different to those using the change factor dataset. However, while the differences were statistically significant at the 95 confidence interval (95CI) (Table 6.3) the difference in the median 80% dry year irrigation demand was generally less than 25 mm, which is the depth of a typical single application of water. The difference in the optimum reservoir capacities was similarly small, though generally >25 mm, with the exception of the Brooms Barn site. These results again suggest that using the UKCP09 WG in place of the conventional change factor, while theoretically leading to more robust decision making, in reality is unlikely to greatly affect the decision outcome because the difference in terms of the action taken is somewhat negligible

Table 6.3. Results of Mann-Whitney U-test statistical analysis comparing 80% dry year irrigation demand and optimum reservoir capacity obtained using economic optimisation with change factor (CF) and UKCP09 WG (WG) datasets, showing median reservoir capacity, whether they are significantly different and using 95 confidence interval (95CI).

Site	Brooms Barn											
Criteria	80% Design dry year irrigation demand						Optimum reservoir capacity					
Emission scen.	Low		Med		High		Low		Med		High	
Data source	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG
Median reservoir capacity	270	280	280	290	270	300	360	310	370	320	370	330
Sig. difference?	Yes		Yes		Yes		Yes		Yes		Yes	
P-value (95CI)	0.00		0.00		0.00		0.00		0.00		0.00	

Site	Slaidburn											
Criteria	80% Design dry year irrigation demand						Optimum reservoir capacity					
Emission scen.	Low		Med		High		Low		Med		High	
Data source	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG
Median reservoir capacity	100	130	110	110	110	120	0	0	0	0	0	0
Sig. difference?	Yes		Yes		Yes		Yes		Yes		Yes	
P-value (95CI)	0.00		0.00		0.00		0.00		0.00		0.00	

Site	Woburn											
Criteria	80% Design dry year irrigation demand						Optimum reservoir capacity					
Emission scen.	Low		Med		High		Low		Med		High	
Data source	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG
Median reservoir capacity	240	270	260	270	260	290	320	300	340	320	340	320
Sig. difference?	Yes		Yes		Yes		Yes		Yes		Yes	
P-value (95CI)	0.00		0.00		0.00		0.00		0.00		0.00	

This result is based on the assumption that the 80% dry year irrigation demand remains the best practice approach. For the irrigation demand case study the optimum reservoir capacity was directly compared with the dry year irrigation demand calculated using a range on probability of non-exceedance values (80%, 85%, 90%, 95% and 100%). Based on these initial findings, the 80% probability of exceedance rule appears to underestimate the optimum reservoir capacity at Brooms Barn and Woburn and overestimate the optimum reservoir capacity at Slaidburn, the wettest site, with a difference of between -120 to +100 mm (Figure 6.6). The 95% probability of non-exceedance rule had a smaller difference of between 0 to + 170 mm. Visual comparison would suggest that the 95% probability of non-exceedance rule is much closer to the optimum reservoir capacity at the sites of Brooms Barn and Woburn. However at the site of Slaidburn, all five probability of non-exceedance rules tested appear to considerably overestimate the optimum reservoir capacity (see Figure 6.6).

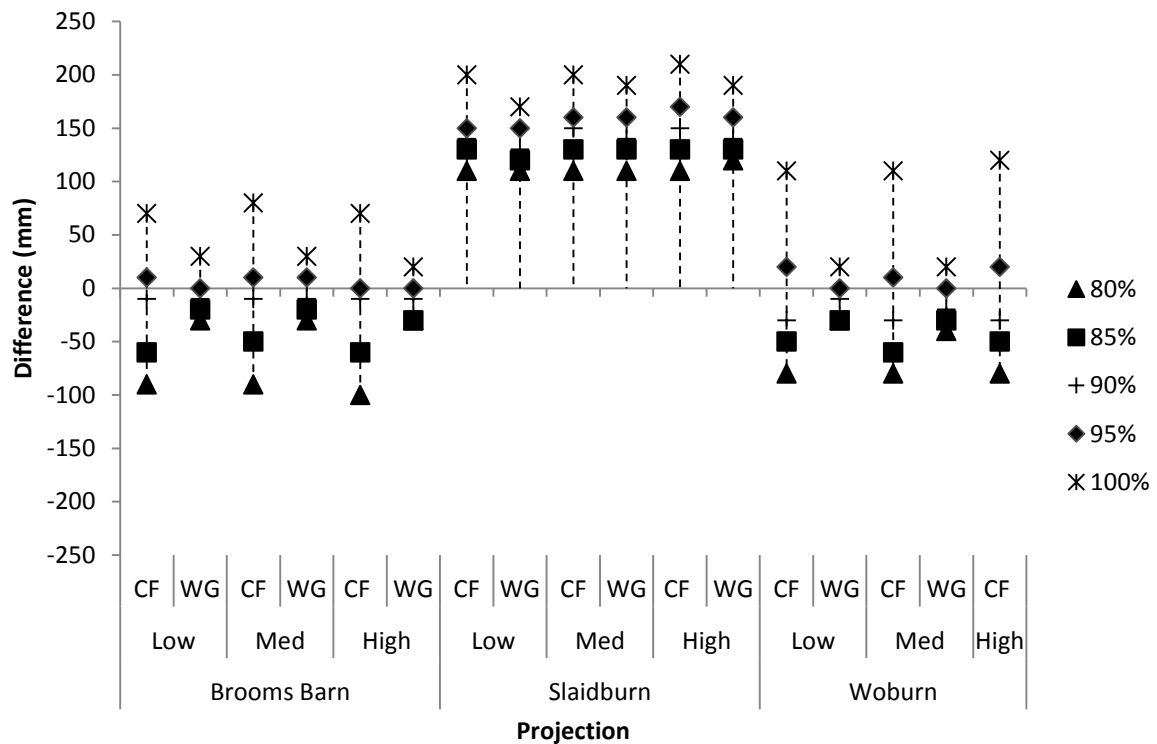


Figure 6.6. Differences between the median dry year irrigation demands using 80% to 95% exceedance rules and the median optimum reservoir capacity, for the change factor (CF) and UKCP09 WG (WG) sequences for each site and emission scenario.

Statistical analysis was also undertaken to establish whether there was significant difference between using the change factor and UKCP09 datasets in terms of 1) maximum daily runoff and 2) the optimum SUDS capacity. The maximum daily runoff values obtained using the UKCP09 WG dataset were significantly different to those from using the change factor dataset with the exception of Woburn low emission scenario. Similarly, the optimum SUDS capacities obtained using the UKCP09 WG dataset were significantly different to those from the change factor dataset at all of the investigated sites and emission scenarios. However, while the differences were statistically significant at the 95 confidence interval (95CI) (Figure 6.5), the difference in the maximum daily runoff was generally less than 500 m³ for the majority of sites and emission scenarios, though exceptions were recorded. The difference in the optimum reservoir capacities was similarly small. These results similarly suggest that using the

UKCP09 in place of the conventional change factor, while theoretically leading to more robust decision making, in reality is unlikely to greatly affect the decision outcome because the difference in terms of the action taken is somewhat negligible.

Table 6.4. Results of Mann-Whitney U-test statistical analysis comparing development maximum daily runoff and optimum SUDS capacity obtained using economic optimisation with change factor (CF) and UKCP09 WG (WG) datasets, showing median maximum runoff, whether they are significantly different and using 95 confidence interval (95CI).

Site	Brooms Barn											
Criteria	Maximum daily runoff						Optimum SUDS storage capacity					
Emission scen.	Low		Med		High		Low		Med		High	
Data source	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG
Median SUDS storage capacity	3740	3900	3750	3920	3670	3970	2400	2700	2450	2700	2400	2750
Sig. difference?	Yes		Yes		Yes		Yes		Yes		Yes	
P-value (95CI)	0.00		0.00		0.00		0.00		0.00		0.00	

Site	Slaidburn											
Criteria	Maximum daily runoff						Optimum SUDS storage capacity					
Emission scen.	Low		Med		High		Low		Med		High	
Data source	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG
Median SUDS storage capacity	5320	5640	5400	5710	5520	5770	4500	4450	4650	4500	4750	4550
Sig. difference?	Yes		Yes		Yes		Yes		Yes		Yes	
P-value (95CI)	0.00		0.00		0.00		0.00		0.00		0.00	

Site	Woburn											
Criteria	Maximum daily runoff						Optimum SUDS storage capacity					
Emission scen.	Low		Med		High		Low		Med		High	
Data source	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG
Median SUDS storage capacity	3410	3420	3360	3490	3630	3470	2200	2400	2200	2300	2350	2450
Sig. difference?	No		Yes		Yes		Yes		Yes		Yes	
P-value (95CI)	0.746		0.00		0.00		0.00		0.00		0.00	

The results of the irrigation reservoir case study are dependent on several assumptions including 1) discount rate, 2) earth work costs and 3) monetary benefit of the water. Each of these variables is a potential source of uncertainty and may potentially affect the optimum reservoir capacity. As a result, a sensitivity analysis was undertaken to establish whether altering these parameters changed the perceived optimum reservoir capacity.

The sensitivity analysis is presented here for the site of Woburn, for the medium emission scenario and the UKCP09 WG dataset. Similar results were obtained for the other sites and emission scenarios using the change factor dataset. The optimum reservoir capacity was largely insensitive to the discount rate, evident from the near horizontal line, with larger discount rates slightly favouring smaller reservoirs. The reservoir capacity was more sensitive to earthworks costs, with larger earthworks costs favouring smaller reservoirs, again as expected. The value of the water in the reservoir had the largest effect on the optimum reservoir capacity; below £0.78.m⁻³ the reservoir produced a negative NPV and was no longer economically viable at this site. Increasing the value of water above £1.56.m⁻³ had little effect on the optimum reservoir capacity, increasing it by only 9.7% even up to a value of £4.68.m⁻³; this reflects the point that useful capacity is limited by demand, with decreasing returns on additional capacity.

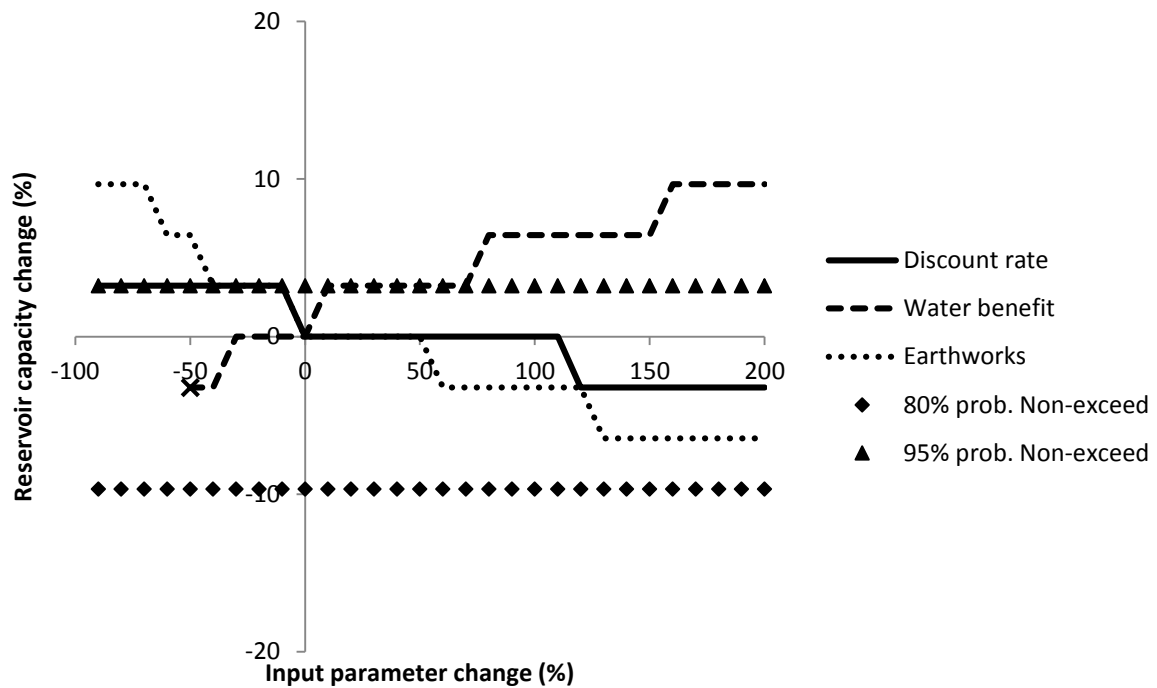


Figure 6.7 Sensitivity analysis comparing optimum reservoir capacity against discount rate, water benefit and earthworks cost, showing changes relative to base parameter values, for the Woburn site and medium emission scenario. The 80% and 95% dry year irrigation demands are also shown for comparison.

These variations in median optimum reservoir capacity were subsequently compared to the capacities given by the simpler % exceedance rules, in this case the 80% and 95% dry year irrigation demand. For the Woburn site and the base variable values, the 95% probability of non-exceedance rule out performs the 80% probability of non-exceedance rule (Figure 6.7). At larger discount rates ($>7\%$) the 80% rule works better, and for lower earthwork costs, less than $\text{£}1.80.\text{m}^{-3}$ the two rules are equally close. For all water values, the 95% probability of non-exceedance rule was nearer the optimum value, but both rules failed to show that the reservoir was no longer economically viable when the water value was less than $\text{£}0.78.\text{m}^{-3}$. More case studies would be needed to confirm these are general results, but they suggest that the 80% rule may be misleading.

It should be noted that these findings are conditional on the view that the median optimum reservoir capacity of the 10,000 sequences represents the most appropriate course of action, akin to the 'Laplacian' school of thought (French

1986). Decision makers who are particularly risk averse or risk seeking may disagree with this assumption and may instead use the quartile or even best/worst case projections, though for the vast majority of stakeholders our stated assumptions should suffice.

6.6 Discussion

GCMs providing ‘high’ resolution daily projections are few in number and those which do are considered less accurate (Palutikof et al., 1997; Huth et al., 2001). As a result, GCM climate change projections often need to be downscaled both spatially and temporally before they can be of any use for decision makers. Numerous downscaling approaches are available, including but not limited to the change factor approach and UKCP09 WG considered here. Different downscaling techniques come with their own advantages and disadvantages. The UKCP09 WG is theoretically the better choice when compared with the conventional change factor approach, given that it allows for non-stationary variability to be simulated and thus incorporated into climate change risk assessments and adaptation planning (Harris et al., 2012).

The UKCP09 WG is however not without its flaws, a previous study by Tham et al., (2011) found that the weather generator initially released with UKCP09 was unable to reproduce observations of key climate variables including sunshine duration and solar irradiation. In later versions of the UKCP09 WG, modifications were made to the UKCP09 WG to improve its predictive capabilities, which were later verified by Eames et al., (2012). It is suspected that the UKCP09 WG will be gradually improved over time to reduce or eliminate any of the outstanding concerns (Harris et al., 2012); while they did not affect the findings of this study they may have implications for other applications where hourly data is of high importance.

Alternatively, the change factor approach may be used although it is subject to its own limitations such as assuming that the temporal and spatial structure of future precipitation and evapotranspiration remains unchanged (Diaz-Nieto and Wilby, 2005; Fowler et al., 2005; Minville et al., 2008; Harris et al., 2012). In some situations, it is necessary to evaluate changes in climate variability and not just

changes in means (Semenov et al., 1998). Despite this, the change factor approach remains popular because of its simplicity and is useful for converting monthly change factors into daily projections needed to model most hydrological processes without incurring excessive expense (Minville et al., 2008).

Large differences in asset NPV of both irrigation reservoirs and SUDS obtained using the change factor approach and UKCP09 WG series were recorded. However, the difference in terms of the action taken, based on the median optimum outcome was comparatively small for both case studies. This result, contrary to other studies such as Harris et al., (2012) suggest that the additional uncertainty considered by the UKCP09 WG, which in theory should lead to more robust decision outcomes actually had a negligible impact, as both irrigation reservoirs and SUDS were found to be relatively insensitive. In the case of irrigation reservoirs, this result is easy to explain as the additional day to day variability simulated by the UKCP09 WG did not have a large impact on the soil moisture deficit, used to calculate the irrigation demand and subsequently the irrigation reservoir capacity required. In the case of the SUDS, this result is less easy to explain, but can on part be attributed to the decision to use the median projection to inform the SUDS design. The UKCP09 WG had a large impact on the annual maximum series, but this result was more extreme for a small proportion of the WG runs, the difference between the change factor and UKCP09 WG series based on the median projection remained relatively small. Other results of this study should serve as a warning to those stakeholders who do not consider the underlying economics of their decision; blind use of probability of non-exceedance rules such as the 80% dry year irrigation demand can lead to maladaptation with stakeholders either over-designing or under-designing their assets to varying degrees based on the site in question and emission scenario used.

6.7 Conclusions

This study found that use of a UKCP09 WG did not greatly alter the decision outcome compared to using the conventional and relatively crude change factor approach, suggesting that the changes in day-to-day climate variability that are

simulated only by the UKCP09 WG are not significant enough to warrant action when informing irrigation reservoir and SUDS design. This result is contrary to the expectation that the UKCP09 WG lends itself to more robust decision making; in reality the difference between the two approaches is somewhat negligible.

The core benefits of the UKCP09 WG may continue to make it an attractive tool to use, those being that it provides hourly climate data and readily available evapotranspiration data. Whether these benefits outweigh its fundamental limitations including the poor simulation of extreme meteorological events, is subject to the sensitivity of each application and the user's requirements. The results of this chapter also found that the irrigation reservoir 'best-practice' approach of using the 80% probability of non-exceedance rule is inadequate and designers should instead investigate the fundamental economics that underpin the decision making process.

CHAPTER 7. OPTION APPRAISAL: DECISION MAKING UNDER UNCERTAINTY

7.1 Overview

This chapter begins by discussing the merits and limitations of current decision criteria under uncertainty. A novel decision criteria and accompanying decision framework is subsequently presented, providing a step by step example of its application. This novel decision criterion is then critically compared against existing decision criteria, its contribution to decision making and climate change adaptation is discussed.

7.2 Background

7.2.1 Introduction

There is considerable uncertainty surrounding the extent and severity of future impacts associated with climate change and the success of mitigation efforts. However, even if mitigation efforts are successful, climate change would continue for the foreseeable future due to the past release of GHG and the inertia of the climate system. The apparent ‘failure’ of high profile climate change protocols in recent years such as the Kyoto protocol has made adaptation planning a much more attractive concept (Anderson and Bows, 2011; Fung et al., 2011; Sanderson et al., 2011; Harris et al., 2012). Mitigation will take several decades for their full effects to be felt, whereas adaptation planning has a much shorter lead time (Meehl et al., 2007). Unlike mitigation, adaptation planning can take place on a local and regional scale, and success is less dependent on the actions of others. Yet despite information on the benefits of adaptation planning being widely available and well documented, in the UK at least relatively few real-world cases of climate change adaptation planning have been recorded outside of government led initiatives (Füssel, 2007; Ranger et al., 2010; Tompkins et al., 2010). Elsewhere in the world, while adaptation has been recorded, it is generally limited to high income (developed) nations, has been viewed as inadequate and is seldom undertaken in response to climate change alone (Adger et al., 2009; Berrang-Ford et al., 2011; Chen et al., 2004). This limited uptake has been

attributed to a variety of factors including the availability, accessibility and willingness to use information, availability of resources, leadership, legal and procedural feasibility and many more, see Moser and Ekstrom, (2010) for a more comprehensive discussion.

It has been suggested that this limited uptake has been compounded by difficulties detecting a definitive climate change signal. Climate change impacts may emerge before we can formally detect them from the background signal due to the relative weak signal to noise ratio of climate change at the scale relevant for decision making compared with the large inter annual variability of rainfall and river flows (Diermanse et al., 2010; Murphy et al., 2011). Trend detection and attribution has also been hampered by other factors including urbanisation, arterial drainage and changes in monitoring practices (Kundzewicz and Robson, 2004; Radziejewski and Kundzewicz, 2004; Svensson et al., 2005; Wilby et al., 2008; Fowler and Wilby, 2010; Murphy et al., 2011). In the UK, attempts have been made to establish when formal detection of trends will be possible (Murphy et al., 2011). For example, a study for the 2020s suggested that changes of approximately 25% of runoff would need to occur for formal detection to be possible in the most sensitive basins, with much larger changes needed across basins exhibiting considerable variability (Wilby, 2006).

In spite of the uncertainty, some form of anticipatory adaptation planning will almost certainly be needed to prevent potential damage and/or loss of life. Despite the substantial uncertainty surrounding future climate change, decisions still need to be made, without which potential impacts may be far more damaging. These decisions should not be based on a single best guess about the future climate, in case it later proves to be wrong. Decisions based on a single optimized view of the future climate can deteriorate rapidly due to small deviations from the projected climate. Using a larger number of scenarios, while better, may still miss most of the future climate's richness (Walker et al., 2013) and provides no systematic way to examine their implications (Dessai and Hulme, 2007; Goodwin and Wright, 2010; McInerney et al., 2012).

7.2.2 Uncertainty and risk

Adaptation, like any decision problem, may be represented as a series of options, with different outcomes for each possible future state, amongst which a decision maker must choose the option which provides the “best” outcome (Tversky and Kahneman, 1986). Options can refer to both soft and hard solutions such as promoting education or building new infrastructure, outcomes refer to the payoff associated with these options and states refer to potential futures which may occur. Two distinct fields of decision theory are widely acknowledged (French, 1986), namely decision making under risk and decision making under uncertainty.

A decision problem is said to be one of risk if a probability distribution can be realistically assigned to the potential states. The most well-known theory in this field is expected utility theory (Von Neumann and Morgenstern, 1945). Expected utility theory is however not necessarily appropriate where potential states are beyond the realms of human experience, as can be the case with climate change. As a decision method, it generally requires more data than can be realistically obtained by decision makers (Froyen, 2005; Polasky et al., 2011). Furthermore, it has been widely criticised as a descriptive theory, with numerous paradoxes emerging which disagree with its core assumptions, well known examples of which can be found in Allais, (1953) and Ellsberg, (1961).

In the field of adaptation planning, decision makers often find themselves in situations of decision making under uncertainty “in which analysts do not know or the parties to a decision cannot agree upon (1) the appropriate models to describe interactions among a system’s variables, (2) the probability distributions to represent uncertainty about key parameters in the models, and/or (3) how to value the desirability of alternative outcomes” (Walker et al., 2013, p.958). A variety of decision criteria have been developed to address problems of decision making under uncertainty, discussions of which can be found here and in Chrisholm and Clark, (1993), Bouglet and Vergnaud, (2000) and more recently Ranger et al., (2010). In addition to several well-known decision criteria including Laplace (Laplace and Simon, 1951), Maximin (Wald, 1945), Maximax, Hurwicz’s

criterion (Hurwicz, 1951) and Minimax regret (Savage, 1951), decision makers can generate problem-specific criteria using Multi-attribute utility theory (MAUT) or Multi-criteria analysis (MCA) (Dyer et al., 1992). MAUT and MCA consist of a wide range of methods, but in general the principle remains the same, options are compared using several criteria that are weighted to produce a single criterion. Alternatively, the criteria can be assigned a score and an aggregated score is then calculated. Some of these criteria can be used with existing decision methods for managing uncertainty, well-known examples of which include Info-gap theory (Ben-Haim, 2001; Ben-Haim, 2006), real option analyses (Amram and Kulatilaka, 1999) and Robust decision making (Lempert and Groves, 2010). Here, criteria refer to the metrics used to compare options and identify the optimum decision outcome, typically by maximizing an objective function or satisficing constraints, whereas decision methods describe the steps by which these decision criteria are applied.

All the above methods can be separated into one of four non-mutually exclusive categories (1-4) (Walker et al., 2013). (1) Resistance approaches prepare plans around the worst case future simulation or precautionary principle. They can be very costly to implement and are not immune to surprises or “black swans” (Taleb, 2007). (2) Resilience approaches accept that some degree of short term damage is inevitable and instead focus on ensuring recovery is rapid. (3) Static robustness approaches typically use a myriad of models or sensitivity analyses as opposed to a single best estimate, to reduce possible vulnerability by selecting those actions which are robust to a large number of potential outcomes. Finally, (4) dynamic robustness approaches prepare plans that are flexible and which can be altered accordingly as new information emerges.

For the purpose of climate change adaptation planning, the vast majority of decision criteria rely on the decision maker having access to future climate change projections, which in the UK is UCKP09 (Murphy et al., 2011). The large number of projections available within the UKCP09 probabilistic dataset, some 10,000 per emission scenario, may in some cases present a ‘barrier to entry’ for some decisions makers. A previous study by Green and Weatherhead, (2014c)

found that a number of decision criteria that are applied in situations of uncertainty have been shown to be incompatible with sub-samples of the probabilistic dataset. Decision criteria using a single projection to inform the decision outcome such as Maximin and Maximax have proved very difficult to obtain from small samples that are consistent with the complete probabilistic dataset.

As a result of the large data requirements of decision methods under risk and the apparent limitations of some criteria for decision making under uncertainty, alternative decision criteria which are more compatible with the UKCP09 probabilistic climate change projections should be sought.

7.3 Objective

The purpose of this chapter was to examine the implications of using different decision criteria with probabilistic climate change projections and in turn develop a novel decision criteria to assist robust decision making, using a case study of irrigation reservoir and SUDS design at three sites in the UK on the basis of the 2050s low, medium and high emission scenarios. The sole objective of this chapter is thus 1) critically compare five current decision criteria and in turn develop a novel improved decision criterion, which supports **robust decision making** in situations of **deep uncertainty**.

7.4 Methodology

All five decision current criteria were evaluated using the full UKCP09 probabilistic ensemble and sub-samples of it to ensure the decision outcome calculated using each criterion could be reliably reproduced from sub-sampling. The novel decision criterion is initially described, it was designed to be simple to implement, support sensitivity analysis and be compatible with the UKCP09 probabilistic dataset and samples of it, to ensure it is suitable for real world decision making, though the criterion presented in theory is applicable to all situations and other countries where multiple competing, though equally plausible, projections are available. If their probabilities are different but available, the decision maker can calculate an outcome for each state by multiplying the

probability of the state by the payoff, the best course of action can then be determined using any of the criteria shown here.

The methodology is presented in three stages; firstly five current decision criteria are described and their criticisms discussed. Secondly, an improved decision criterion is outlined. Thirdly, all of the decision criteria are applied to simplified real-world problems of designing an irrigation reservoir to meet the water demands of a potato crop in addition to building and maintaining SUDS to manage future runoff for the 2050s using climate change projections taken from UKCP09.

7.4.1 Current decision criteria

This study considered five decision criteria that are typically employed in situations of uncertainty; these are Laplace, Maximax, Maximin, Hurwicz's criterion and Minimax regret. Laplace is based on the principle of insufficient reason which assumes that all potential states are equi-probable in the absence of knowledge of event probability i.e. it assumes that there is no reason to favour one state over another. It identifies the best option as the option which yields the largest average expected outcome based on all the potential states. Maximin identifies the best option as the option which provides the largest expected outcome from the worst possible state. In contrast, Maximax identifies the best option as the option providing the largest outcome from the best possible state. The best option under Hurwicz's criterion is calculated using a weighted average of Maximin and Maximax with the weighting defined by α , representing the optimism of the decision maker. Minimax regret identifies the option with the smallest regret, representing the difference between the best and worst possible outcomes across all states. Readers are directed to Ranger et al., (2010) for practical examples of applying these criteria.

A general criticism levelled against all of these criteria is that all are "rationalised on some notion of ignorance" (Froyn, 2005, p. 204). It has previously been suggested that none of the current decision criteria are as 'good' as one might wish (French, 1986). It seems highly unlikely that all five criteria (Laplace, Maximin, Maximax, Hurwicz and Minimax regret) are equal, and there must exist

some way to evaluate which is best. This view led to the development of a set of axioms, which reflect 'good' properties of decision making criteria, and which may be used to formally assess which is optimal (French, 1986). If we accept the axiom basis of a criterion we should in theory accept its implications. However, none of the popular criteria are validated by all the axioms of decision theory and in fact it is not possible for any criterion to satisfy all of the axioms; see (French, 1986) for formal proof. As opposed to assessing our criterion against French's original axioms of decision theory (French, 1986), the wider criticisms surrounding these criteria and examine whether or not they are suitable for use with the UKCP09 probabilistic climate change projections were explored.

With regards to Laplace, two fundamental criticisms have emerged, namely that it is too restrictive in its design and that the principle of insufficient reason which states that all states are equally likely is "by no means as innocuous as it might appear" (French, 1986, p. 218). It has previously been suggested that it is rare (though not impossible) for no information to exist regarding the likelihood of states occurring, thus the premise of scenario symmetry i.e. all scenarios are equally likely is arguably flawed and with it the principle itself (French, 1986). Laplace was further criticised by Knight, (2012) who suggested that blind use of this approach can lead to absurd conclusions. Maximin and by extension Hurwicz's criterion have been criticised for being too crude; Maximin in particular is considered to be overly pessimistic as an approach and not suitable for real world decision making (Etner et al., 2012). Minimax regret can be similarly criticised, the values of regret used to determine the optimal decision are not absolute but strictly relative, and as a result the decision outcome can be altered easily by introducing irrelevant or flippant options.

However, since the probability of the occurring event is unknown, it is reasonable to assume in situations of deep uncertainty that any projection is just as likely as any other. As a result, a core assumption of this study is that the probability distribution is considered to be uniform, akin to the 'Laplacian' view of decision making under uncertainty which is consistent with emerging guidelines (Environment Agency, 2013). While this may remain a point of contention for

some individuals, the alternatives which would require us to generate subjective probabilities for each of the UKCP09 projections or omit projections that are perceived as unlikely are not advisable.

Current decision criteria, such as Maximax and Maximin, typically fit the decision maker to a specific rational model. In the case of Maximin, this rational model describes an individual that is particularly pessimistic, while Maximax describes an individual that is very optimistic. Laplace, in theory, represents a “neutral” viewpoint. A hypothetical problem, comparing three irrigation solutions, termed option A, B and C, across a discrete number of states is shown for demonstration (Figure 7.1). These options may represent entirely different solutions such as installing a new water delivery system, building an on-site reservoir, replacing a sewer network with larger capacity pipes or installing SUDS to manage future runoff. Alternatively, they may represent options which are subtly different such as building a lined and unlined reservoir or constructing a pond or detention basin. Figure 7.1 was generated by ranking the outcome of three options from smallest to largest across a discrete number of states. In this (hypothetical) example, the average outcomes of options A, B and C happen to be equal. As such, Laplace would view these options as equal. Whilst there is nothing intrinsically wrong with this, real decision makers can and regularly do depart from this idealised sense of the rational decision maker. For example some optimistic decision makers may perceive option A to be the best because it could provide the largest outcome. Pessimistic decision makers may perceive option C to be the best because it has the smallest negative outcome. Other decision makers may prefer option B because it has a smaller number of states with a negative outcome.

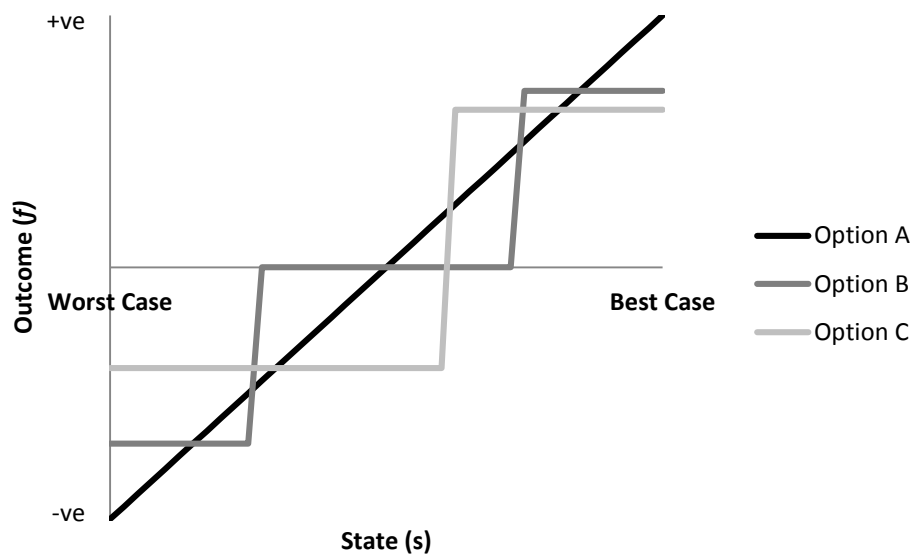


Figure 7.1 Hypothetical problem comparing three options against a discrete number of states. Average outcome of option A, B and C are equal (not actual data).

7.4.2 Developing a novel decision criterion

Given the acknowledged limitations with the criteria discussed, an attempt was made to develop a novel discussion criterion, hereby termed the Green Z-score, which considers all the potential options, outcomes and states, and hence is amenable to sub-sampling of the complete probabilistic dataset.

Unlike Laplace, which uses a single rational model to describe all decision makers, the Green Z-score uses three parameters to generate a simplified rational model that can be personalised to the individual decision maker, in many ways similar to MCA. MCA was selected as the basis for the Green Z-score as it places the focus on choice behaviour, enabling decision makers to resolve trade-offs in a transparent, audible and analytically robust manner (Hajkowicz, 2008). The parameters underpinning the Green Z-score consist of the coefficient of optimism (α), the coefficient of robustness (β), and a user defined threshold of acceptability (t). The coefficient of optimism is used to describe how optimistic the decision maker is about the future, specifically whether they are more concerned about the negative or positive outcomes associated with a particular decision.

The coefficient of robustness (β) is used to quantify how “robust” the decision maker wants their option to be, specifically whether they are more concerned about the overall performance of option across all states or merely those states where the option performs exceptionally better than all other options. The threshold of acceptability is used to define the boundary between acceptable and unacceptable outcomes.

The Green Z-score for each option is calculated using a weighted difference between its overall performance, calculated across all states, and its negative performance, calculated across those states where the outcome falls below the threshold of acceptability. The weighting is determined by the coefficient of optimism α . The optimal decision outcome is then the option with the highest Green Z-score.

This concept of a coefficient of optimism (α) can be traced back to Hurwicz’s criterion which uses a similar criterion to describe how optimistic an individual is about the future. In Hurwicz’s weighted criterion model, the decision outcome is obtained using a weighted average of Maximin and Maximax, and hence only considers the payoffs from extreme states, which may not be considered in sub-samples of the complete probabilistic dataset. To calculate the Green Z-score, Maximin and Maximax in Hurwicz’s original model have been substituted with two alternative parameters. These parameters, termed the overall performance and negative performance respectively, are summed across all states, providing a value for each option.

7.4.3 Green Z-score equation

The mathematical definition of the Green Z-score is represented as:

$$z_d = \max_{d \in D} \left((\alpha \cdot A) - ((1 - \alpha) \cdot B) \right) \quad (7-1)$$

Where:

z_d = decision outcome

d = option, D = options

α = coefficient of optimism (where $0 < \alpha \leq 1$)

A = overall performance (see EQ (7-2))

B = negative performance (see EQ (7-3))

$$A = \sum_{s=1}^{s=n} \left(\frac{(f_d - \chi)}{(\max_{d \in D} f_d - \chi)} \right) \quad (7-2)$$

Where:

f_d = option outcome

s = state

$$\chi = \left(\max_{d \in D} f_d - \left(\left(\max_{d \in D} f_d - \min_{d \in D} f_d \right) \cdot \left(\frac{\beta}{100} \right) \right) \right)$$

β = coefficient of robustness

$$B = \sum_{s=1}^{s=n} \left(\frac{(f_d - t)}{(\min_{d \in D} f_d - t)} \right) \quad (7-3)$$

Where:

f_d = option outcome

s = state

t = threshold of acceptability (e.g. 0)

7.4.4 Green Z-score practical example

A practical example of Green Z-score is provided to guide readers through its calculation. The following decision problem compares three options (option X, Y and Z) with different outcomes (f_d) across 11 discrete states (s). The minimum ($\min_{d \in D} f_d$) and maximum payoff ($\max_{d \in D} f_d$) of all three options for each state is also shown (Table 7.1).

Table 7.1 Sample data

State (s)	Option X	Option Y	Option Z	$\max_{d \in D} f_d$	$\min_{d \in D} f_d$
1	-10	-15	-3	-3	-15
2	-8	-15	-3	-3	-15
3	-6	-15	-3	-3	-15
4	-4	0	-3	0	-4
5	-2	0	-3	0	-3
6	0	0	-3	0	-3
7	2	0	3.6	3.6	0
8	4	0	3.6	4	0
9	6	15	3.6	15	3.6
10	8	15	3.6	15	3.6
11	10	15	3.6	15	3.6

The following **parameters** are used (Table 7.2):

Table 7.2 Parameter set

Coefficient of optimism (α)	Coefficient of robustness (β)	Threshold of acceptability (t)
0.5	80	0

All workings are provided for **option X only**, all options are summarised at the end of the section along with the **decision outcome**.

The **overall performance (X)** is then calculated (Table 7.3):

Table 7.3 Overall performance A, option X

State	f_d	$\max_{d \in D} f_d$	$\min_{d \in D} f_d$	$\left(\frac{\beta}{100}\right)$	$\left(\max_{d \in D} f_d - \left(\left(\max_{d \in D} f_d - \min_{d \in D} f_d\right) \cdot \left(\frac{\beta}{100}\right)\right)\right)$
1	-10	-3	-15	0.80	-12.60
2	-8	-3	-15	0.80	-12.60
3	-6	-3	-15	0.80	-12.60
4	-4	0	-4	0.80	-3.20
5	-2	0	-3	0.80	-2.40
6	0	0	-3	0.80	-2.40
7	2	3.6	0	0.80	0.72
8	4	4	0	0.80	0.80
9	6	15	3.6	0.80	5.88
10	8	15	3.6	0.80	5.88
11	10	15	3.6	0.80	5.88

State	f_d	$\max_{d \in D} f_d$	$\min_{d \in D} f_d$	χ	$(f_d - \chi)$	$(\max_{d \in D} f_d - \chi)$	$\left(\frac{(f_d - \chi)}{(\max_{d \in D} f_d - \chi)}\right)$
1	-10	-3	-15	-12.60	2.60	9.60	0.27
2	-8	-3	-15	-12.60	4.60	9.60	0.48
3	-6	-3	-15	-12.60	6.60	9.60	0.69
4	-4	0	-4	-3.20	*	*	*
5	-2	0	-3	-2.40	0.40	2.40	0.17
6	0	0	-3	-2.40	2.40	2.40	1.00
7	2	3.6	0	0.72	1.28	2.88	0.44
8	4	4	0	0.80	3.20	3.20	1.00
9	6	15	3.6	5.88	0.12	9.12	0.01
10	8	15	3.6	5.88	2.12	9.12	0.23
11	10	15	3.6	5.88	4.12	9.12	0.45
Total							4.75

**This value is not calculated because $f_d < \chi$*

The **negative performance (B)** is initially calculated (Table 7.4)

Table 7.4 Negative performance B, option X

State	f_d	t	$(f_d - t)$	$\min_{d \in D} f_d$	$\min_{d \in D} f_d - t$	$\left(\frac{(f_d - t)}{(\min_{d \in D} f_d - t)} \right)$
1	-10	0	-10	-15	-15	0.67
2	-8	0	-8	-15	-15	0.53
3	-6	0	-6	-15	-15	0.40
4	-4	0	-4	-4	-4	1.00
5	-2	0	-2	-3	-3	0.67
6	0	0	*	-3	*	*
7	2	0	*	0	*	*
8	4	0	*	0	*	*
9	6	0	*	3.6	*	*
10	8	0	*	3.6	*	*
11	10	0	*	3.6	*	*
Total						3.27

* This value is not calculated because $f_d > t$

Table 7.5 Green Z-score

Option	A	B	$(\alpha.A)$	$((1 - \alpha).B)$	$(\alpha.A) - ((1 - \alpha).B)$
X	4.75	3.27	2.37	1.63	0.74
Y	6.00	3.00	3.00	1.50	1.50
Z	4.94	3.35	2.47	1.68	0.79

The decision outcome (z_d) is **Option Y** because it has the highest Green Z-score.

7.4.5 Calculating the Green Z-score

The overall performance of each option is calculated first as follows. The effective outcome range of all options is calculated for each state. This is the difference between the maximum outcome and minimum outcome across all options, multiplied by the coefficient of robustness, $\beta/100$ (where $0 \leq \beta \leq 100$). This value is then deducted from the maximum outcome to calculate the minimum bound of the effective range. If absolute robustness is sought a β value of 100 is used, in which case the effective outcome range is the full 0-100% outcome range i.e. max-min outcome for each state. If a β value of 50, is used, the effective

outcome range is the 50-100% effective outcome range (i.e. max-median outcome for each state). The outcome of each option is then normalised against the effective outcome range for each state. If the outcome of an option is equal to the maximum bound of the effective range for that state i.e. it has the best outcome it assigned a value of 1. If the outcome of an option is equal to the minimum bound of the effective range for that state i.e. it has the worst outcome, it is assigned a value of 0. Options in between are assigned a value of 0 to 1 depending on their position relative to the maximum outcome and minimum bound of the effective range. If the outcome of an option is less than the minimum bound, which can occur if $\beta < 100$ it is assigned a value of 0. The overall performance of each option is then obtained by summation across all states.

The negative performance of each option is then calculated for each state. The user defined threshold of acceptability (t) can be any value between the max and minimum outcome. Decision makers who are particularly risk adverse may use a high threshold, while those that are particularly risk seeking may use a low threshold. The acceptability range considering all available options is then calculated; this represents the difference between the threshold and the minimum outcome across all options. If the outcome of an option is less than this threshold then it is counted against the option's Green Z-score i.e. it is considered undesirable. The payoff of each option is then normalised against the acceptability range. If the outcome of an option is equal to the minimum bound of the acceptability range for that state, i.e. it has the worst outcome, it is assigned a value of 1. If the outcome of an option is equal to the maximum bound of the acceptability range for that state, i.e. it equals the threshold value, it is assigned a value of 0. Options in between are assigned a value of 0 to 1 depending on their position relative to the minimum bound and the maximum bound of the acceptability range. If the outcome of an option is greater than the maximum bound (which can occur if $t < \max f$) it is not counted towards the negative performance of that option. The negative performance of each option is then obtained by summation across all states.

The Green Z-score is then calculated by multiplying the overall performance by α (representing the coefficient of optimism) and deducting the negative performance multiplied by $1-\alpha$. The option yielding the largest Green Z-score is then selected as optimal.

7.4.6 Applying the Green Z-score in practice

The Green Z-score was subsequently calculated using the above methodology for all irrigation reservoir and SUDS capacities for all three sites and emission scenarios and the optimal irrigation reservoir and SUDS capacities compared to those obtained using current decision criteria.

7.5 Results

With neutral parameter values, the optimal reservoir and SUDS capacities from the Green Z-score and Laplace were largely similar (Table 7.6). The optimal irrigation reservoir capacity based on the Green Z-score was within 25 mm of Laplace, with the Green Z-score generally suggesting a slightly smaller capacity. Maximin typically resulted in no reservoir being built. Maximax resulted in much larger reservoir capacities compared to all other decision criteria. At all three sites the optimal SUDS capacity based on the Green Z-score was identical to Laplace, highlighting the strong similarities between these two decision criteria (Table 7.7). The range of decision outcomes based on each criterion highlights the considerable uncertainty in the probabilistic dataset while the difference between the criteria reflects the fundamental differences between them.

Table 7.6 Optimum irrigation reservoir capacity (mm) obtained using a selection of current decision criteria for the three sites and three emission scenarios. Results obtained from 10,000 future projections for each emission scenario for each site. Each sequence generated from a perturbed observed series using monthly change factors taken from UKC09 10000 sample ensemble 2050s time slice. Hurwicz calculated using $\alpha=0.5$. Green Z-score calculated using coefficient of robustness $\beta=100$, threshold of acceptability $t=0$, coefficient of optimism $\alpha=0.5$.

Site Emission scenario	Brooms Barn			Slaidburn			Woburn		
	L	M	H	L	M	H	L	M	H
Laplace	390	410	400	0	0	0	360	380	390
Maximin	0	0	0	0	0	0	0	0	0
Maximax	600	620	650	280	310	330	530	580	620
Minimax regret	420	450	430	100	120	140	380	420	440
Hurwicz	560	590	600	270	300	300	510	540	570
Green	370	390	380	0	0	0	340	360	370

Table 7.7 Optimum SUDS capacity (m³) obtained using a selection of current decision criteria for the three sites and three emission scenarios. Results obtained from 10,000 future projections for each emission scenario for each site. Each sequence generated from a perturbed observed series using monthly change factors taken from UKC09 10000 member ensemble 2050s time slice. Hurwicz calculated using $\alpha=0.5$. Green Z-score calculated using coefficient of robustness $\beta=100$, threshold of acceptability $t=0$, coefficient of optimism $\alpha=0.5$.

Site Emission scenario	Brooms Barn			Slaidburn			Woburn		
	L	M	H	L	M	H	L	M	H
Laplace	2500	2450	2500	4600	4750	4850	2450	2400	2550
Maximin	1500	1900	1600	3950	3950	3800	1800	1800	1800
Maximax	3800	3600	4000	5550	5400	6250	5050	4500	4800
Minimax regret	2750	2550	2900	4800	5000	5300	3600	3350	3650
Hurwicz	3050	2850	3100	5000	5100	5700	4600	4450	4750
Green	2500	2450	2500	4600	4750	4850	2450	2400	2550

7.5.1 Sensitivity to extreme projections

The optimal irrigation reservoir and SUDS capacities obtained using each decision criteria was subsequently compared when using progressively fewer climate change projections, sequentially excluding the extreme outcomes. This was undertaken to establish how sensitive the optimal irrigation reservoir and SUDS capacities associated with each decision criteria was to extreme projections within the probabilistic dataset and provide the basis for further analysis of sub-samples of the complete probabilistic dataset. This was achieved by first identifying the optimal irrigation reservoir and SUDS capacities calculated using the complete probabilistic dataset i.e. all 10,000 projections, for each of the decision criteria. For each irrigation reservoir and SUDS capacities, all 10,000 projections were then ranked on the basis of their NPV from smallest to largest. Projections were then systematically removed from the tail ends of the NPV distribution, re-calculating the optimal irrigation reservoir and SUDS capacities after removing each projection, eventually leaving only the median projection.

The results of both case studies for Woburn 2050s medium emission scenario are shown in Figure 7.2. Similar results were obtained from the other sites and emission scenarios for both case studies. Irrigation reservoirs and SUDS capacities calculated using certain decision criteria were particularly sensitive to the inclusion of extreme projections, with clear trends emerging, most notably Maximin and Maximin. Interestingly, Hurwicz tended to give similar results to Maximax despite using a coefficient of optimism of 0.5. This is the result of the number of “good” and “bad” projections contained within the complete probabilistic dataset, they are not equal and as such Hurwicz does not appear halfway between Maximax and Maximin. As additional projections were added and the optimum irrigation reservoir capacity re-calculated (Figure 7.2), all six decision criteria were relatively stable up until 30%, beyond which they begin to diverge, a result mirrored by the SUDS case study. Maximax and Maximin follow an exponential curve, confirming that just a few extreme projections exert a substantial pull on the decision outcome. Maximax and Maximin each use a single extreme projection, best or worst, to inform the decision outcome and so this result was not unexpected. Laplace and Green Z-score were however much

less sensitive, evident from the shallowness of both curves. The key differences between the two case studies are the shapes of the decision outcome curves. Laplace and the Green Z-score were reasonably similar for both case studies, maintaining a near horizontal line. Minimax regret was similarly shaped for both case studies, although the curve is slightly steeper for the SUDS case study suggesting that it more sensitive to the inclusion of extreme projections compared with the irrigation reservoir case study. Comparing the irrigation reservoir and SUDS curves obtained using Hurwicz, both curves were initially similar, although the SUDS curve rapidly steepens nearing using the complete dataset, confirming that a very small proportion (<5%) of the probabilistic projections can have a large impact on the decision outcome. Maximin on the other hand exceeding 80% data inclusion flat lines for the SUDS case study, although this can be attributed to the insensitivity of SUDS design to the inclusion of extreme climate change projections. It was assumed that SUDS as a very minimum were required to meet existing design standards and thus no-action was not deemed an appropriate response, as result the decision outcome using Maximin appears to flat line when using the complete dataset. However, when this assumption was removed the decision outcome appeared to directly mirror the decision outcome using Maximax, highlighting the similarities between both case studies.

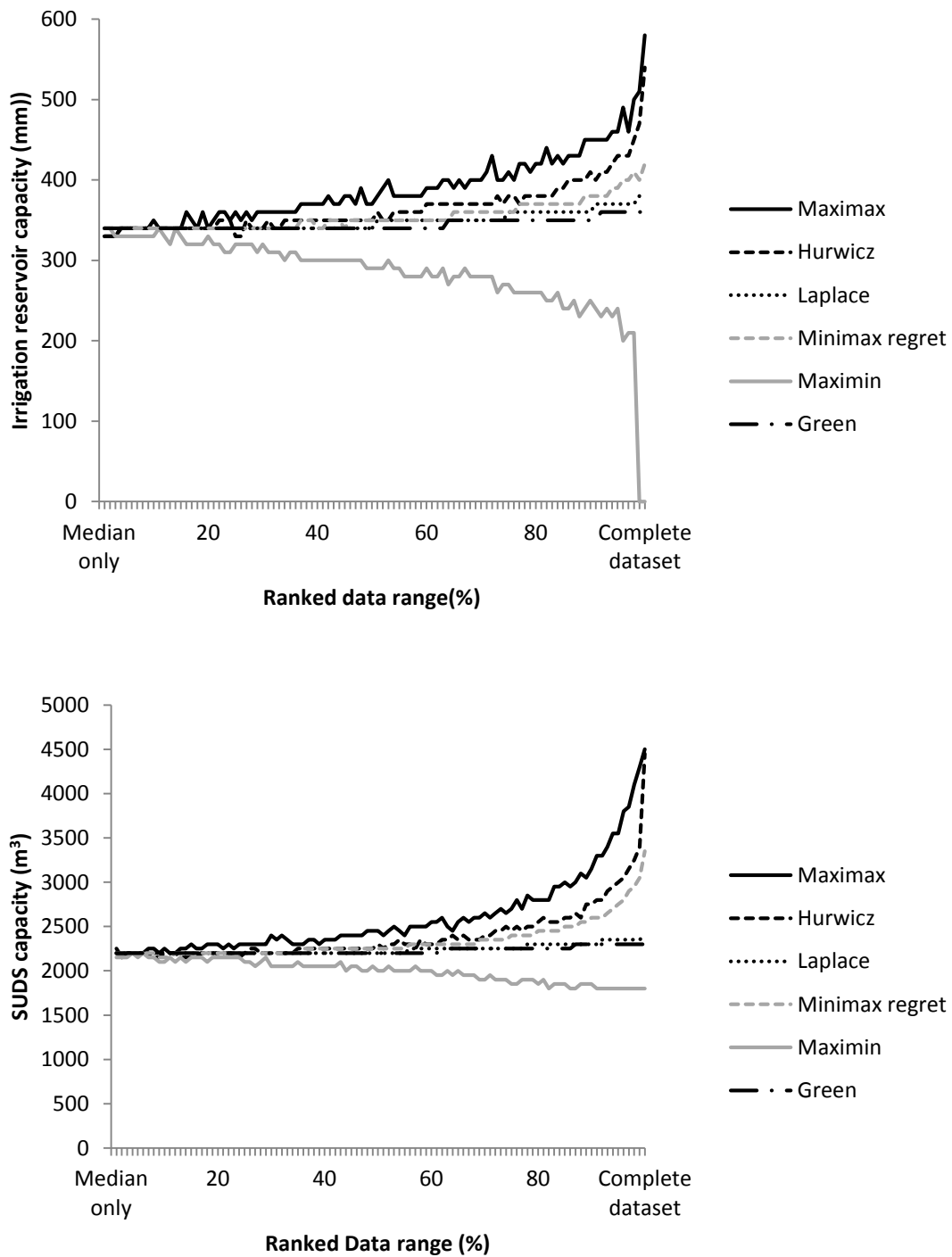


Figure 7.2 Optimal reservoir capacities for various decision criteria generated excluding extreme climate change projections, for the 2050s medium emission scenario. Projections systematically removed in an iterative manner (right to left) starting with the most extreme (min and max NPV respectively), calculating the optimal reservoir capacity at each step. Hurwicz calculated using coefficient of optimism $\alpha=0.5$. Green Z-score calculated using coefficient of robustness $\beta=100$,

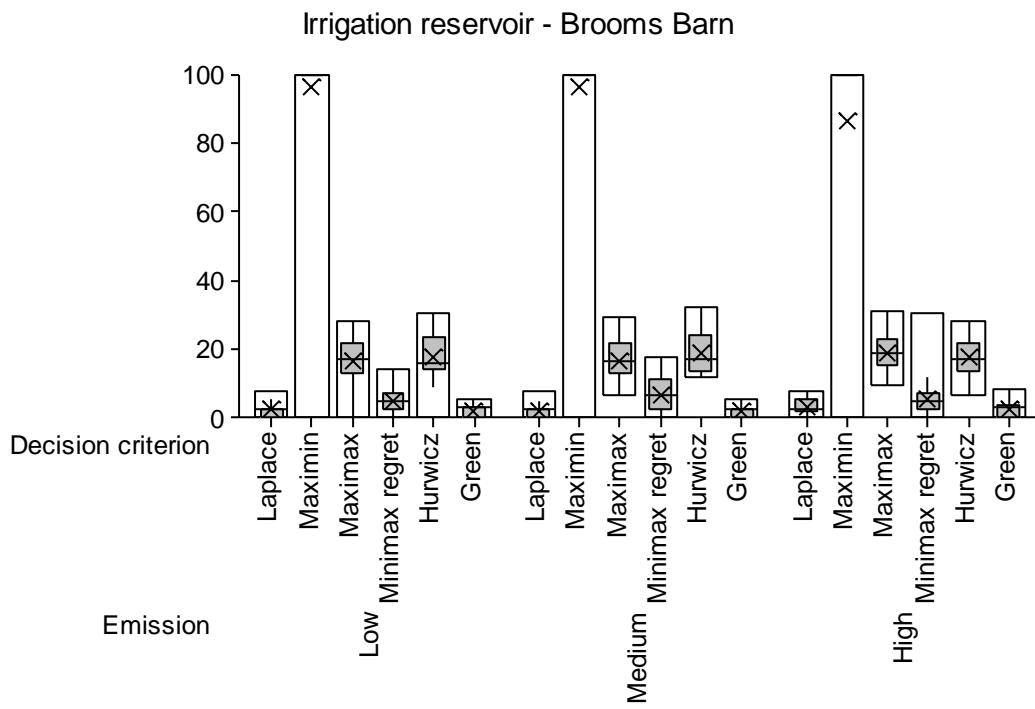
threshold of acceptability $t=0$, coefficient of optimism $\alpha=0.5$. Adapted from Green and Weatherhead, 2014d).

7.5.2 Using sampled data with the Green Z-score

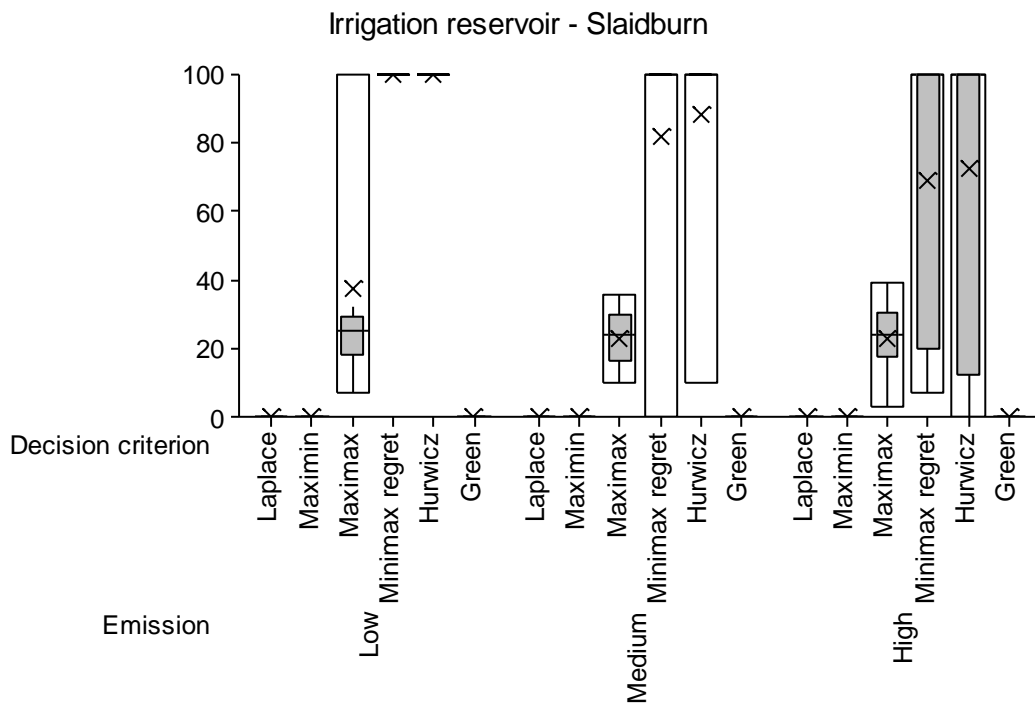
As a result of the complexity of many models, e.g. crop growth simulations, it is often not feasible to use all of the 10,000 sample ensemble, and therefore sampling is frequently used (alternatively, a rapid assessment model may be used, though readers are directed elsewhere for further details see Kwakkel et al., (2012) and Haasnoot et al., (2012). These sampling methods should be carefully designed to ensure they capture extreme projections so as not to bias the decision outcome should certain decision criteria be used. Combining a poorly designed sampling method with a decision criterion that is very sensitive to the inclusion of extreme projections such as Maximin or Maximax can result in very different decision outcomes compared to using the complete probabilistic dataset (Green and Weatherhead, 2014d). Due to the sensitive nature of Maximax and Maximin, and to a lesser extent Hurwicz and Minimax regret, use of these criteria with sub-samples of the complete UKCP09 probabilistic dataset can lead to misleading conclusions (Green and Weatherhead, 2014d). If, for example, the extreme projection is not sampled and thus excluded from the analysis, the result can be a very different sized irrigation reservoir or SUDS.

In order to establish whether the optimum reservoir capacity could be estimated from samples of the complete probabilistic dataset more reliably using the Green Z-score than using the current decision criteria, 30 simple random samples of 30 projections were extracted from the complete probabilistic dataset. The percentage difference between the optimum irrigation reservoir and SUDS capacities obtained using each of the decision criteria with the complete probabilistic dataset and with each sample was calculated (Figure 7.3). Simple random sampling was chosen both for convenience and on the basis of previous findings which suggest it provides similarly rich sub-samples compared to more advance stratified methods with more sub-samples (Green and Weatherhead, 2014d).

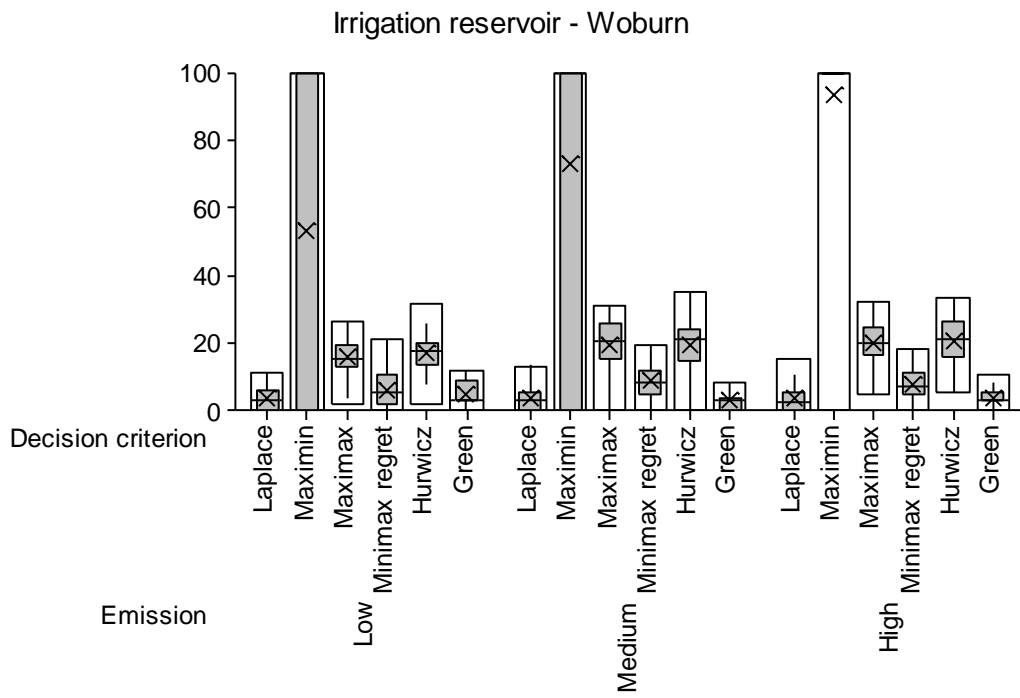
Percentage difference complete dataset and sub-sample (%)



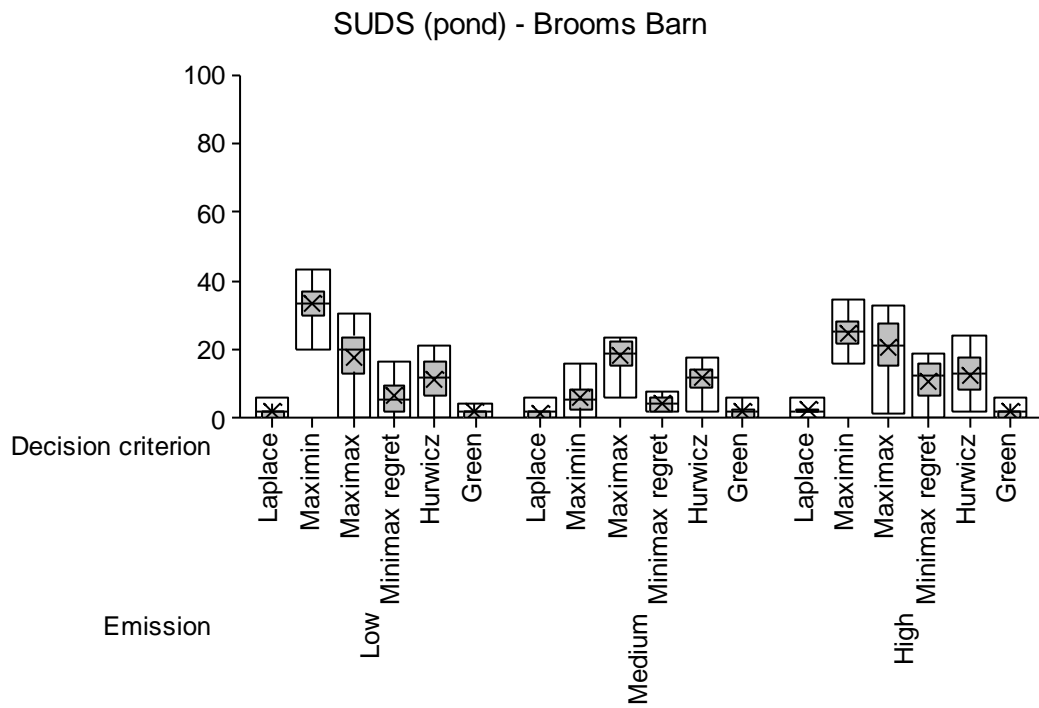
Percentage difference complete dataset and sub-sample (%)



Percentage difference complete dataset and sub-sample (%)



Percentage difference complete dataset and sub-sample (%)



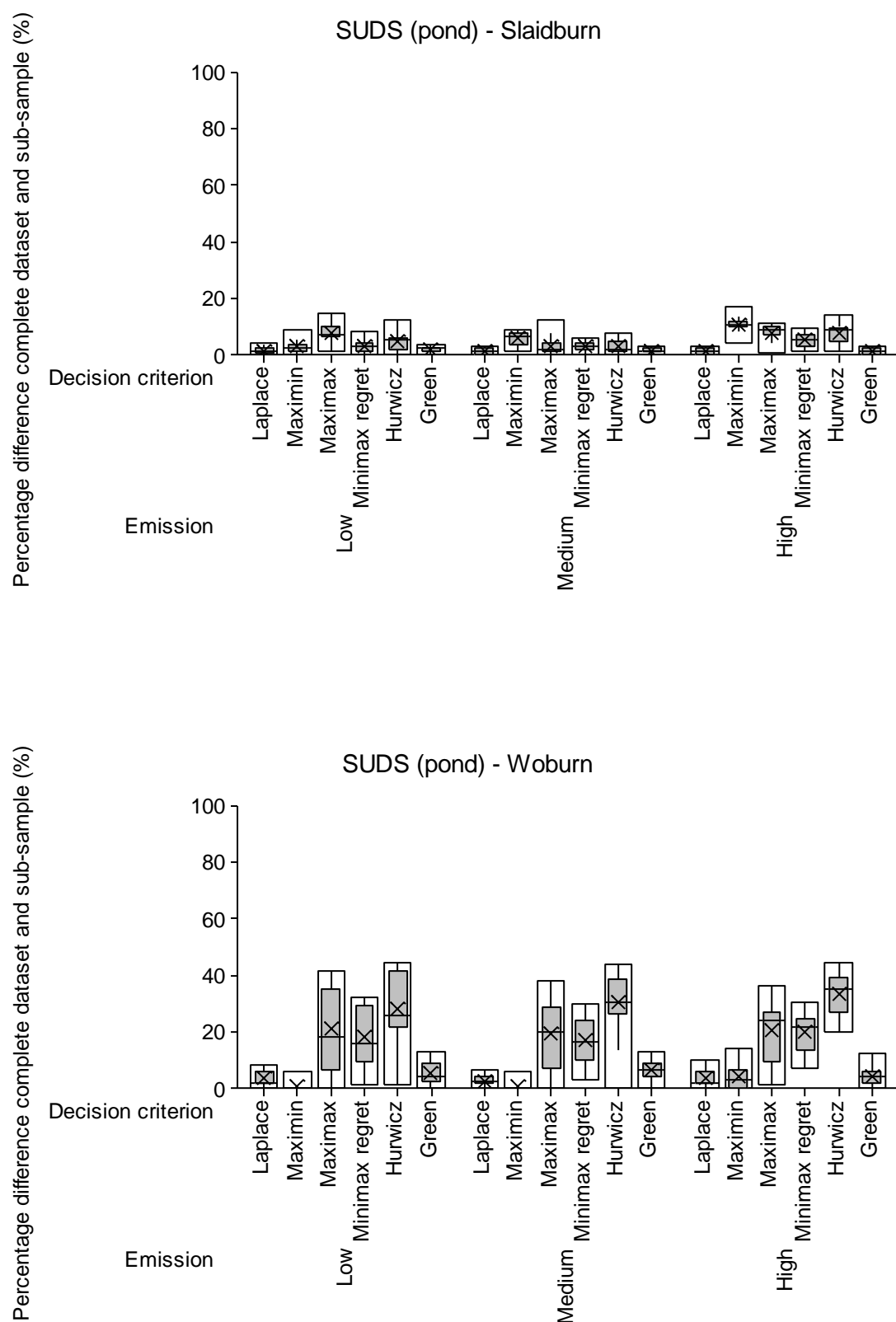


Figure 7.3 Percentage difference in optimal irrigation reservoir and SUDS capacities for each decision criteria using sub-samples of the probabilistic dataset

in place of the complete probabilistic dataset (i.e. all 10000 projections) for Brooms Barn, Slaidburn and Woburn, for the 2050s and three emission scenarios. Results calculated using 30 sub-samples consisting of 30 projections each. Hurwicz calculated using coefficient of robustness $\alpha=0.5$. Green Z-score calculated using coefficient of robustness $\beta=100$, threshold of acceptability $t=0$, coefficient of optimism $\alpha=0.5$. Outliers included (*)

Comparing the three sites overall, all but Laplace and Green show generally poor reproducibility from sub-samples of the complete probabilistic dataset, evident from the large range of percentage differences shown (Figure 7.3). Laplace and Green exhibit the smallest percentage differences, both in terms of median and range, at all three sites. On the basis of the irrigation reservoir case study, Maximin exhibited the largest maximum percentage difference at Brooms Barn and Woburn, though at Slaidburn it appears to perform as favourably as Green and Laplace; however, this result can be attributed to the low irrigation demand combined with the worst case rational model underpinning Maximin, which in this example always favoured building no reservoir. In contrast, the irrigation reservoir capacities obtained using Maximax at Brooms Barn and Woburn were generally reproduced well from sub-sampling, however at Slaidburn, they were poorly reproduced, a result which can be attributed to the small number of positive irrigation reservoir scenarios for this particular site. In terms of the SUDS case study, all of the decision criteria were reproduced reasonably well from sub-sampling, though some less so, most notably Maximin at Brooms Barn and Maximax, Hurwicz and Minimax regret at Woburn.

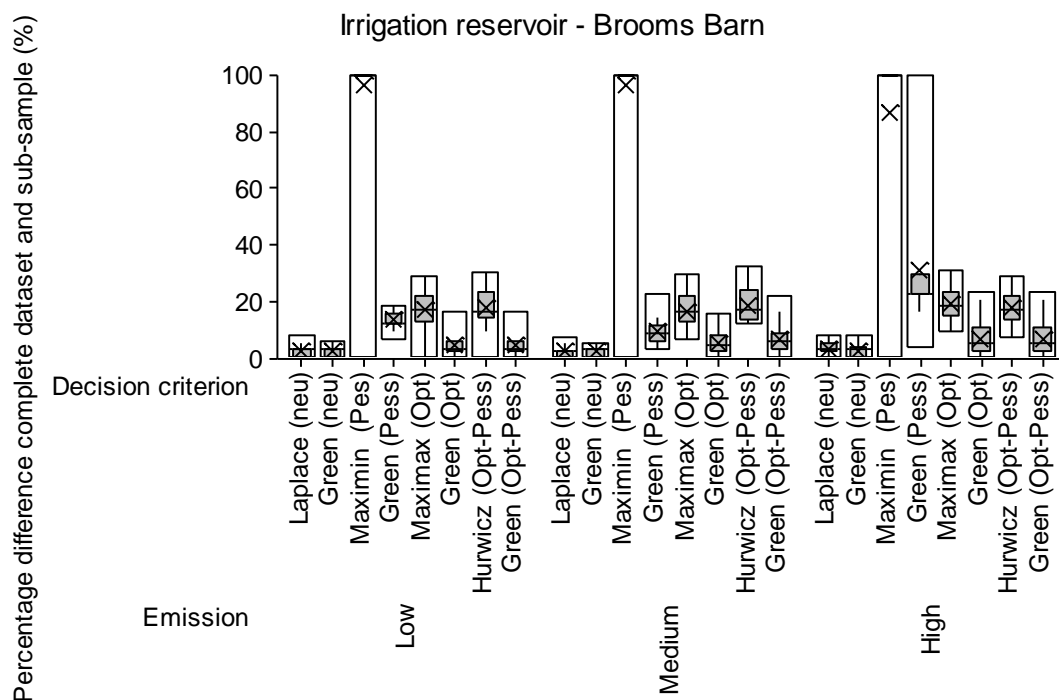
On the basis of these initial results, the Green Z-score produced comparable results to Laplace with sampling. This can be largely attributed to the similar methods used by each criterion. Both criteria utilise multiple projections to inform the decision outcome. However, the advantage of the Green Z-score compared to Laplace is that it allows different risk appetites to be accommodated. The parameters underpinning the Green Z-score i.e. coefficient of optimism, coefficient of robustness and threshold of acceptability, can be varied to be representative of decision makers expressing differing degrees of optimism and pessimism. To establish whether variations of Green Z-score could produce more

consistent results than current decision criteria from sub-samples, the optimal reservoir and SUDS capacity was calculated for the Green Z-score using parameters representative of individuals who would typically prefer Laplace, Maximin, Maximax or Hurwicz's criterion, (Table 7.8), and for each of the decision criteria, using the complete dataset and each of the 30 samples of 30 projections. It was not possible to compare decision outcomes from the Green Z-score against Minimax regret due to the fundamental differences between these two decision criteria.

Table 7.8 Green Z-score parameter setup, showing four decision criteria regularly employed in situations of uncertainty along with four variations of Green Z-score representative of different types of decision maker including the neutral., pessimist, optimist and optimist-pessimist

Decision maker	Decision criterion	Green Z-score parameters		
		Coefficient of optimism (α)	Coefficient of robustness (β)	Threshold of acceptability (t)
Neutral	Laplace	0.5	100	0
Pessimist	Maximin	0.01	100	0
Optimist	Maximax	1	0.01	0
Optimist-Pessimist	Hurwicz	0.5	0.01	0

The percentage differences in the optimum irrigation reservoir and SUDS capacities between the complete dataset and the sub-samples was then calculated, showing the difference in terms of the decision outcome associated with each of the decision criteria and each variation of the Green Z-score. The results for Brooms Barn for both case studies are shown in Figure 7.4.



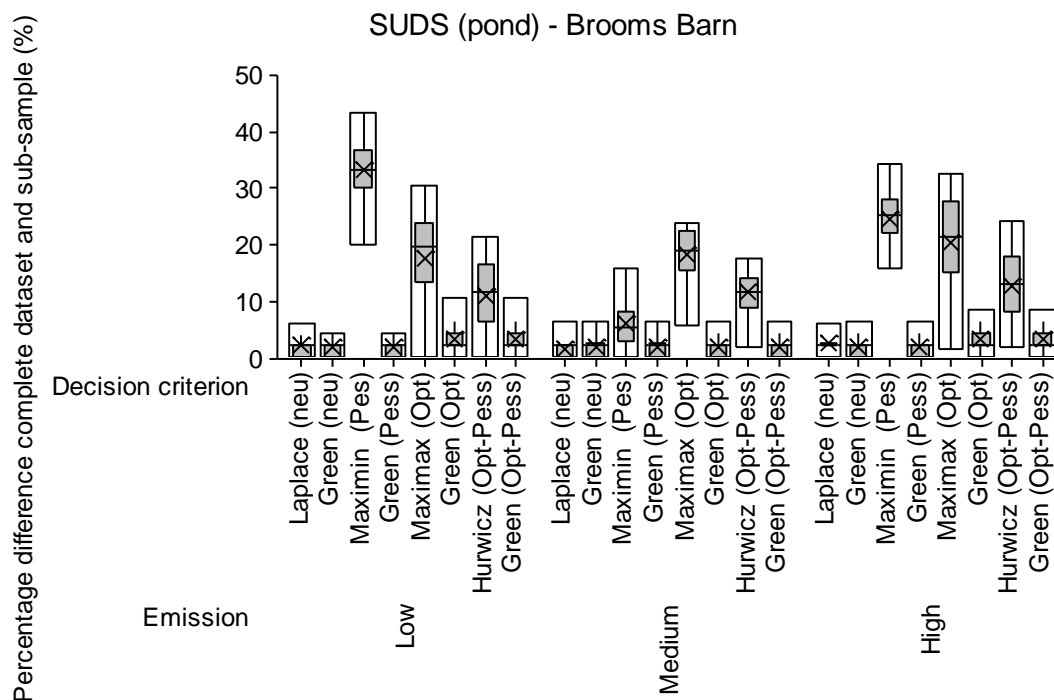


Figure 7.4 Percentage difference in optimal irrigation reservoir and SUDS capacities for each of the decision criteria using sub-samples of the probabilistic dataset in place of the complete probabilistic dataset (i.e. all 10000 projections) for Brooms Barn for the 2050s and three emission scenarios. Results calculated using 30 sub-samples consisting of 30 projections each. Hurwicz calculated using coefficient of robustness $\alpha=0.5$. Green Z-score calculated using coefficient of robustness $\beta=100$, threshold of acceptability $t=0$, coefficient of optimism $\alpha=0.5$. Outliers included (*) Four different categories of decision maker (DM) assumed; neutral., pessimist, optimist and optimist-pessimist, each category containing two decision criteria; a current decision criterion and a variation of Green Z-score.

At all three sites and all three emission scenarios, the optimum irrigation reservoir capacity from the full dataset was reproduced better from sampling using the Green Z-score than when using any of the other decision criteria. At Brooms Barn, the Green Z-score has a smaller median and range percentage difference compared to current decision criteria. At Slaidburn, the percentage difference between the complete probabilistic dataset and each sub-sample, in terms of the optimal reservoir capacity was zero for every variation of Green Z-score. In contrast, the percentage difference for Hurwicz and Maximax was greater and

has a much larger range, suggesting that that they would be poorly reproduced from sub-sampling. At Woburn, Green Z-score largely outperformed current decision criteria, while the percentage difference ranges were comparable; the median percentage difference is smaller for Green Z-score compared to current decision criteria. For the SUDS case study, the percentage difference between the complete dataset and sub-sample for all the decision criteria was generally smaller than the equivalent irrigation reservoir case study. The largest percentage differences were recorded when using Maximin and to a lesser extent Maximax, Laplace and the Green Z-score were however similarly reproduced well from sub-sampling.

7.6 Discussion

Numerous decision methods and criteria have been developed to assist with decision making under risk and under uncertainty (Ranger et al., 2010). Methods of decision making under risk are not suitable for adaptation planning as the climate change projections on which adaptation is based are not provided with a probability of occurrence (Polasky et al., 2011). In the UK, advances in modelling capabilities and a greater appreciation of uncertainty (Stainforth et al., 2007; Tebaldi and Knutti, 2007) have provided decision makers with a “legitimate and credible” suite of climate change projections in the form of UKCP09 (Tang and Dessai, 2012). However, these advances have come at the expense of saliency. It has previously been suggested that over time climate science may become too complex and thus inhibit decision makers from making sensible decisions, reflected in the perceived saliency gap associated with UKCP09 (McNie, 2007; Sarewitz and Pielke Jr, 2007; Tribbia and Moser, 2008). The diversity of users and lack of specific guidance on how to use UKCP09 may have diminished its usability. Modelling can result in misleading conclusions if projections are not used correctly. As a result, it has been suggested that the value of UKCP09 for real world decision making is limited (Tang and Dessai, 2012).

UKCP09’s saliency gap can be attributed in part to the move from deterministic to probabilistic methods of communicating climate change information. Unfortunately, this move, aimed at quantifying at least part of the underlying

uncertainty in the climate change projections and discussed elsewhere (Green and Weatherhead, 2014d) has not yet been accompanied by the development of supporting tools and techniques. A large number of criteria which were previously developed to support decision making have shown to be not appropriate for climate change adaptation because they require more information that can be realistically obtained (Froyn, 2005; Polasky et al., 2011) are crude, overly complex (Ranger et al., 2010) or not reproducible from sub-samples of the probabilistic projections (Green and Weatherhead, 2014d).

As a result, a novel decision criterion, the Green Z-score, is developed and applied to a simplified real-world decision problem of designing an on-farm irrigation reservoir. This method is purposely designed to be simple to implement and thereby encourage its use among decision makers that until now were largely reliant on proponents of classical decision theory (French, 1986), some of which are shown here for comparison purposes, to help inform adaptation.

The limitations are consistent with the general criticisms levelled against the incorrect application of MCA (its closest similarity) and cost-benefit analysis (CBA) on which the Green Z-score is based, as opposed to an issue with the criterion itself. MCA is subject to a host a potential pitfalls, stemming from incorrectly defining the problem structure, poor performance data, inappropriate capturing of decision-maker preferences, incorrect application of additive utility and duplication or overlapping criteria (Hajkowicz, 2008). The majority of criticisms levelled against MCA are generally associated with the incorrect application of the method as opposed to issues with the method itself.

Cost Benefit Analysis (CBA), which forms the basis of the analysis underpinning the Green Z-score has previously been criticised because it does not generally account for interactions between impacts. Certain individuals may feel more strongly about a project if it imposes both environmental and social costs, regardless of whether these effects are valued independently. Non-monetary elements can also present their own challenges for CBA which may make the Green Z-score less suitable, however these elements can sometimes be valued using hedonic pricing (Pearson et al., 2002), travel cost methods (Chen et al.,

2004) or other non-market value methods. A further limitation of CBA and by extension the Green Z-score is the time and resources it takes to estimate the financial benefits of an action. However, it can be argued that the time the effort required to estimate financial benefits is proportional to the relative costs of taken said action. “For example, where a tidal barrier is protecting hundreds or thousands of properties, a proportionate amount of effort in estimating monetised benefits would be justified” (Environment Agency, 2013, p.3). However, while Green Z-score does suffer from some of the limitations of CBA it also borrows a number of positive elements from MCA, specifically its greater flexibility and its ability to resolve trade-offs in a transparent, audible and analytically robust manner. Similarly, Green Z-score can be combined with Monte-Carlo simulation to explore the wider uncertainties and ensure decision outcomes are robust (Dorini et al., 2011). Further work, testing the real-world application of the Green Z-score and whether or not it is preferred to conventional decision criteria with actual decision makers is however recommended.

One of the greatest challenges associated with UKCP09 and its uptake is the sheer number of climate change projections provided. Many impact models are limited by the number of projections they can realistically handle. Some organisations do not have the available resources to utilise these projections, notably in instances where climate change impacts tend to be wide ranging and the potential solutions very diverse. As a result, sample analysis was undertaken to ensure Green Z-score can be reliably reproduced from small sub-samples of the UKCP09 probabilistic dataset and as such is suitable for real-world practice.

7.7 Conclusion

Consistent with previous findings, this study found that a number of current decision criteria should not be used with sub-samples of the UKCP09 probabilistic dataset on account that the decision outcomes obtained from them tend to differ substantially to the complete dataset. Certain methods, including Laplace, whose outcomes are successfully reproduced from small samples, are subject to their own criticisms and limitations, both in their assumptions and rational model. Other criteria give different results depending on the sample.

Many of the current decision criteria including Laplace and Maximin assume a fixed rational model; such models are rarely accommodating of all decision makers attitudes, particularly when working in the realms of climate change where uncertainty abounds. The apparent lack of flexibility in current decision criteria may account for their limited uptake. While their use has been previously advocated for adaptation planning, it is much harder to develop a real world case for using them with the current suite of probabilistic climate projections owing to their practical limitations. The Green Z-score, unlike many of the current decision criteria considered here, provides reproducible decision outcomes from sub-samples of the UKCP09 dataset and can accommodate a host of differing risk appetites.

CHAPTER 8. UNCERTAINTY: A SUMMARY

8.1 Overview

The chapter begins by summarising the impact of uncertainty to decision making for local water management. A series of summary results tables are provided detailing the key findings of this research.

8.2 Background

8.2.1 Introduction

In spite of vast and seemingly irreducible natural, economic and social uncertainty, decision still need to made, without which outcomes may be far more damaging, even catastrophic (Walker et al., 2003). However, as a result of the globalisation of issues and the interrelationships that have formed between systems, making the incorrect decisions can have significant implications (Walker et al., 2003). It is increasingly accepted, that uncertainties exist in all policy making situations, however while the concept of uncertainty is by large universally accepted, the different dimensions of uncertainty, their characteristics, impact on decision making and methods for dealing with them is less well understood. Methods of describing and dealing with uncertainty developed partly in response to the concept of the “precautionary principle”, placing uncertainty “more firmly and explicitly on the political agenda” (Walker et al., 2003, p.2). The precautionary principle was designed to address uncertain situations where incorrect action or lack of action can result in harm of humans and the environment. It is one of the founding principles underpinning the EU’s Water Framework Directive (WFD) which emphasises the importance of considering uncertainty in water management. However, overreliance on the precautionary principle can lead to dissatisfactory outcomes, actions can be incredibly costly, inadvertently hamper competitiveness and slow development and innovation by placing regulatory burdens on industry. The principle has been widely criticised for being vague and “cost blind”, “how precautionous should I be?” is a common question and one that cannot necessarily be answered (Sunstein, 2005). The precautionary principle can take the form of anticipatory action or pre-damage control, however in order to be successful this form of actions warrants an uncertainty assessment to be incorporated into the decision making process (Refsgaard et al., 2007). Uncertainty assessments of models used for

the purpose of supporting water management decisions are vital (Beven and Binley, 1992; Beven, 2002; Pahl-Wostl, 2002; Jakeman and Letcher, 2003; Refsgaard and Henriksen, 2004; Pahl-Wostl, 2007; Vandenberghe et al., 2007).

8.2.2 Uncertainty

A recent shift from acknowledging and understanding uncertainty (Van Der Sluijs, Jeroen P et al., 2005; Ascough li et al., 2008) to classification of different types of uncertainties has been acknowledged (Regan et al., 2002). Uncertainty typologies attempt to characterise the different types of uncertainty and in doing so aim to foster understanding and identification of uncertainty during risk characterisation (Skinner et al., 2013). Uncertainty typologies and terms such as error, risk and ignorance are defined and interpreted differently by different authors (see Walker et al., 2003; Skinner et al., 2013 for example). The various definitions and typologies on offer highlight the fundamental differences between different disciplines awareness and interpretation of uncertainty. For example Funtowicz and Ravetz, (1990) offer generic definitions, Beck, (1987) offer sector specific definitions, Klauer and Brown, (2004) definitions emerged as a result of discussions between social scientists and natural scientists and Skinner et al., (2013) offer typologies based on large evidence base of 171 peer-reviewed environmental risk assessments. Existing uncertainty typologies, based on small-scale literature reviews (Regan et al., 2002) and amalgamations of existing frameworks (Ascough li et al., 2008) are typically overlapping, contradictory and subjective (Skinner et al., 2013). However, in all cases, a distinction is typically made between bounded and unbounded uncertainty, the former implies a situation in which all states and outcomes are known and the latter implies a situation in which some or all of the states are unknown. All probabilities are assumed to be known in situations of bounded reality, elsewhere referred to as “statistical uncertainty” (Walker et al., 2003). Level of uncertainty describes the spectrum of knowledge exists, ranging from an “unachievable ideal of complete deterministic understanding” at one end and at the opposite end of the spectrum, total ignorance (Walker et al., 2003). Decision makers regularly occupy an area in this spectrum between knowing everything and knowing nothing, as a result their ultimate goal should be to make decisions which reduce undesirable impacts from surprises or “black swans” instead of aiming to eliminate them completely.

Uncertainty typologies may be distinguished by their location, Walker et al., (2003) distinguishes between several sources of uncertainty including context, model, inputs, parameter and model outcome uncertainty. Context uncertainty refers to the identification of the system boundaries to be modelled and the proportion of the real world that is inside the system. Model uncertainty is typically separated into model structure uncertainty and model technical uncertainty, the former of which refers to uncertainty about the form of the model itself or its conceptual model and the latter refers to uncertainty arising from the implementation of the model within the computer. Input uncertainty refers to uncertainty related to the description of the reference system and the forces that control it. Input uncertainty is typically distinguished into controllable and uncontrollable inputs depending on the capabilities of the decision maker to alter the input variables. Parameter uncertainty refers to uncertainty stemming from the data and methods used to calibrate model parameter. Finally model outcome uncertainty is the accumulated uncertainties associated with the model outcomes of interest to the decision maker, and it is this source of uncertainty that we are most interested in as it determines what level of action is deemed appropriate (Walker et al., 2003).

Numerous approaches have been developed to cope with uncertainty; it is in the interest of decision makers to select approaches which match the level of uncertainty. For example, very uncertain situations warrant robust plans which are insensitive to uncertainties and will succeed in a variety of situations or plans which are flexible that can be altered as new information emerges. In the case of the precautionary principle, an appropriate level of proof based on the level of uncertainty should be decided, to determine whether action is deemed necessary to avoid large scale and or irreversible harm to people or the environment. Scenarios and their use in policy analysis, is one way to deal with uncertainties stemming from the external environment of a system, often its future environment. For a scenario to be deemed plausible, it must be founded on a “coherent and internally consisting set about key relationships and driving forces e.g. technology changes, prices” (Walker et al., 2003, p.8). It is important to stress that scenarios do not forecast what will happen in the future but instead provide an indication of what might happen i.e. they provide plausible futures. As a result scenarios are not verifiable and because of this it is generally accepted that use of scenarios, as is the case with UKCP09, is beyond the realms of statistical uncertainty

(Walker et al., 2003). Scenario uncertainty is a more appropriate term for the situation we currently find ourselves in, whereby there is a range of possible outcomes but the mechanisms surrounding their formulation is not well enough understood and as a result it is not possible to formulate a probability for any one outcome (Walker et al., 2003).

8.3 Methodology

In order to evaluate the impact of different sources of uncertainty on adaptation and explore whether having access to more data and a greater appreciation of uncertainty alters the way we make decisions, each of results of the previous chapters were simultaneously compared using a normalised relative impact score (NRI) (0-100). These sources of uncertainty include 1) emission scenario uncertainty, 2) 10,000 sample ensemble uncertainty (represented by the difference between using the complete 10,000 sample ensemble and a single “most likely” deterministic projection), 3) 11SCP uncertainty (represented by the difference between the using the complete 10,000 sample ensemble and the 11SCP), 4) sub-sampling uncertainty (represented by the difference between using the complete 10,000 sample ensemble and sub-samples of it, using different sampling methods) and 5) downscaling uncertainty (represented by the difference between the 10,000 sample ensemble change factor dataset and the UKCP09 WG). Details of their computation are provided below for each source of uncertainty considered by this research.

8.3.1 Calculating the relative impact of emission scenario uncertainty

The decision outcome obtained using each of the decision criteria was calculated for each site and emission scenario, including the novel decision criterion presented here. An absolute difference was then calculated by comparing the difference between decision outcomes obtained using different emission scenarios. For example, using the high emission scenario instead of the low emission scenario in combination with Laplace to design an irrigation reservoir at Brooms Barn resulted in an absolute difference of 20 mm. Whereas, using the medium emission scenario instead of the high emission scenario with the same criterion resulted in an absolute difference of only 10 mm. The absolute difference of each decision outcome was then normalised on a scale of 0-100 using the absolute difference range of the sources of uncertainty considered by this research i.e. 0 having the smallest impact on the decision outcome,

100 having the largest impact on the decision outcome. Details of the impact of emission scenario uncertainty for all of the decision criteria, at Brooms Barn are shown in Table 8.1, along with summary bullet points detailing the main results for all three sites.

8.3.2 Calculating the relative impact of the UKCP09 sample ensemble uncertainty

An absolute difference was calculated by comparing the difference between each decision outcome using only the median or “most likely” decision outcome, representing a deterministic projection of the future climate, and using the complete 10,000 sample ensemble. For example, using the “most likely” decision outcome instead of the complete 10,000 sample ensemble in combination with Laplace to design an irrigation reservoir at Brooms Barn for the low emission scenario resulted in an absolute difference of 30 mm. Similarly, using the “most likely” decision outcome instead of the complete 10,000 sample ensemble in combination with Laplace for the high emission scenario resulted in an absolute difference of 30 mm. The absolute difference of each decision outcome was similarly normalised on a scale of 0-100 using the absolute difference range of all of the sources of uncertainty considered here. Details of the impact of moving from a “most likely” deterministic projection of the future climate to using the complete 10,000 sample ensemble, and thus a wider appreciation of the uncertainty considered by UKCP09, for all of the decision criteria, at Brooms Barn for both case studies are shown in Table 8.2, along with summary bullet points detailing the main results for all three sites.

8.3.3 Calculating the relative impact of the 11SCP uncertainty

An absolute difference was calculated by comparing the difference between decision outcomes obtained using the 11SCP and the 10,000 sample ensemble. For example using the 11SCP instead of the 10,000 sample ensemble in combination with Laplace to design an irrigation reservoir at Brooms Barn for the low emission scenario resulted in an absolute difference of 40mm. Based on the medium emission scenario, with the same criterion, this difference increased to 60. The absolute difference of each decision outcome was similarly normalised on a scale of 0-100 using the absolute difference range of all of the sources of uncertainty considered here. Details of the impact of using the 11SCP instead of the complete 10,000 sample ensemble for all of

the decision criteria, at Brooms Barn are shown in Table 8.3, along with summary bullet points detailing the main results for all three sites.

8.3.4 Calculating the relative impact of sub-sampling uncertainty (using different sampling methods)

An absolute difference was calculated by comparing the difference between using the complete 10,000 sample ensemble, and sub-samples of just 30 projections, obtained using various sampling methods. For example using 30 projections selected at random (from the 10,000 sample ensemble) instead of the complete 10,000 sample ensemble in combination with Laplace to design an irrigation reservoir at Brooms Barn for the low emission scenario resulted in an absolute difference of 0mm. In contrast, using optimum Latin hypercube sampling instead of random selection, using the same emission scenario and decision criterion resulted in an absolute difference of just 10mm. The absolute difference of each decision outcome was similarly normalised on a scale of 0-100 using the absolute difference range of all of the sources of uncertainty considered here. Details of the impact of the impact of sub-sampling the 10,000 sample ensemble, using different sampling methods is shown, at Brooms Barn are shown in Table 8.4, along with summary bullet points detailing the main results for all three sites.

8.3.5 Calculating the relative impact of downscaling uncertainty

An absolute difference was calculated by comparing the difference between using the change factor method to downscale the 10,000 sample ensemble and using the UKCP9 WG. For example using the change factor method to downscale the 10,000 sample ensemble instead of the UKCP9 WG in combination with Laplace to design an irrigation reservoir at Brooms Barn for the low emission scenario resulted in an absolute difference in of 40mm. For the medium emission scenario, the difference increases to 50. The absolute difference of each decision outcome was similarly normalised on a scale of 0-100 using the absolute difference range of all of the sources of uncertainty considered here. Details of the impact of downscaling for all of the decision criteria and emission scenarios, at Brooms Brooms for both case studies are shown in Table 8.5, along with summary bullet points detailing the many results for all three sites. In addition, an summary table, providing a side by side comparison of the different sources of uncertainty and their impact on the decision outcome for each

decision criteria for both case study for both dry (Brooms Barn and Woburn) and wet sites (Slaidburn) is provided in Table 8.6. It should be noted, that this research considered only a small number of uncertainties, in order to keep the results concise while still addressing the stated aim of this research, additional relevant comparisons can be made from the results of this chapter using the NRI equations listed in (8-1 and (8-2).

$$NRI_{\substack{\text{irrigation} \\ \text{reservoir}}} = \left(\frac{c_i - \min_{c_i \in C_i} c_i}{\max_{c_i \in C_i} c_i - \min_{c_i \in C_i} c_i} \right) \cdot 100 \quad (8-1)$$

$$NRI_{\text{SUDS}} = \left(\frac{c_s - \min_{c_s \in C_s} c_s}{\max_{c_s \in C_s} c_s - \min_{c_s \in C_s} c_s} \right) \cdot 100 \quad (8-2)$$

Where:

c_i = irrigation reservoir absolute change, D_i = all irrigation reservoir absolute change

d_s = SUDS absolute change, D_s = all SUDS absolute change

For example, the NRI of using the UKCP09 WG instead of the 11SCP with Laplace to design an irrigation reservoir at Brooms Barn for the medium emission scenario can be calculated as per below, implying a small impact on the decision outcome.

$$NRI_{\substack{\text{irrigation} \\ \text{reservoir}}} = \left(\frac{c_i - \min_{c_i \in C_i} c_i}{\max_{c_i \in C_i} c_i - \min_{c_i \in C_i} c_i} \right) \cdot 100 = \left(\frac{10 - 0}{370 - 0} \right) \cdot 100 = 2.70 \quad (8-3)$$

8.4 Results

The following results have been colour coded for ease of reading, a score of <25 (**Green**) implies a low impact on the decision outcome, a score of 25-50 (**Yellow**) implies low-medium impact on the decision outcome, a score of 50-75 (**Orange**) implies a medium-high impact on the decision outcome and a score >75 (**Red**) implies a high impact on the decision outcome. Results are only provided for the site of Brooms Barn **only**. Results were not always consistent for all three sites, as a result summary results for all three sites are provided in the form of bullet points. Result tables for the remaining two sites are provided in Appendix F.1-F.5.

8.4.1 Emission scenario uncertainty summary

Table 8.1 Normalised relative impact score (0-100) attributable to emission scenario uncertainty and decision outcome of irrigation reservoirs (mm) and SUDS (m³) (pond shown) for the site of Brooms Barn. Results obtained using 10,000 sample ensemble change factor dataset. Results for Slaidburn and Woburn are shown in Table F-1.

Irrigation reservoir – Brooms Barn					SUDS (pond) – Brooms Barn				
Laplace					Laplace				
Emission		L	M	H	Emission		L	M	H
		390	410	400			2500	2450	2500
L	390		5.41	2.70	L	2500		1.75	0.00
M	410	5.41		2.70	M	2450	1.75		1.75
H	400	2.70	2.70		H	2500	0.00	1.75	
Maximin					Maximin				
Emission		L	M	H	Emission		L	M	H
		0	0	0			1500	1900	1600
L	0		0.00	0.00	L	1500		14.04	3.51
M	0	0.00		0.00	M	1900	14.04		10.53
H	0	0.00	0.00		H	1600	3.51	10.53	
Maximax					Maximax				
Emission		L	M	H	Emission		L	M	H
		600	620	650			3800	3600	4000
L	600		5.41	13.51	L	3800		7.02	7.02
M	620	5.41		8.11	M	3600	7.02		14.04
H	650	13.51	8.11		H	4000	7.02	14.04	

Irrigation reservoir – Brooms Barn					SUDS (pond) – Brooms Barn				
Minimax regret					Minimax regret				
Emission		L	M	H	Emission		L	M	H
		420	450	430			2750	2550	2900
L	420		8.11	2.70	L	2750		7.02	5.26
M	450	8.11		5.41	M	2550	7.02		12.28
H	430	2.70	5.41		H	2900	5.26	12.28	
Hurwicz					Hurwicz				
Emission		L	M	H	Emission		L	M	H
		560	590	600			3050	2850	3100
L	560		8.11	10.81	L	3050		7.02	1.75
M	590	8.11		2.70	M	2850	7.02		8.77
H	600	10.81	2.70		H	3100	1.75	8.77	
Green					Green				
Emission		L	M	H	Emission		L	M	H
		370	390	380			2450	2450	2450
L	370		5.41	2.70	L	2450		0.00	0.00
M	390	5.41		2.70	M	2450	0.00		0.00
H	380	2.70	2.70		H	2450	0.00	0.00	

- The impact of **emission scenario uncertainty** compared with other investigated uncertainties was **generally larger** at **dry sites** (Brooms Barn and Woburn) and **smaller** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Laplace**.
- The impact of **emission scenario uncertainty** compared with other investigated uncertainties was **generally smaller** at **all sites** when designing irrigation reservoirs compared with SUDS when using **Maximin**.
- The impact of **emission scenario uncertainty** compared with other investigated uncertainties was **generally equal** at **dry sites** (Brooms barn and Woburn) and **generally smaller** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Maximax**.
- The impact of **emission scenario uncertainty** compared with other investigated uncertainties was **generally equal** at **dry sites** and **smaller** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Minimax regret**.

- The impact of **emission scenario uncertainty** compared with other investigated uncertainties was **generally larger** at **dry sites** and **generally smaller** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Hurwicz**.
- The impact of **emission scenario uncertainty** compared with other investigated uncertainties was **generally larger** at **dry sites** and **smaller** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using the **Green Z-score**.

8.4.2 UKCP09 sample ensemble uncertainty summary

Table 8.2 Normalised relative impact score (0-100) attributable to UKCP09 sample ensemble uncertainty and decision outcome of irrigation reservoirs (mm) and SUDS (m³) (pond shown) for the site of Brooms Barn. Results obtained using 10,000 sample ensemble change factor dataset and a median “most likely” decision outcome from economic analysis. Results for Slaidburn and Woburn are shown in Table F-2.

		Deterministic							
		Irrigation reservoir – Brooms Barn				SUDS (pond) – Brooms Barn			
		Emission	Low	Medium	High	Emission	Low	Medium	High
Probabilistic	Laplace	Median decision outcome	360	370	370	Median decision outcome	2400	2450	2400
		capacity (mm)	390	410	400	capacity (m ³)	2500	2450	2500
	Maximin	norm diff.	8.11	10.81	8.11	norm diff.	3.51	0.00	3.51
		capacity (mm)	0	0	0	capacity (m ³)	1500	1900	1600
	Maximax	norm diff.	97.30	100.00	100.00	norm diff.	31.58	19.30	28.07
		capacity (mm)	600	620	650	capacity (m ³)	3800	3600	4000
	Minimax regret	norm diff.	64.86	67.57	75.68	norm diff.	49.12	40.35	56.14
		capacity (mm)	420	450	430	capacity (m ³)	2750	2550	2900
	Hurwicz	norm diff.	16.22	21.62	16.22	norm diff.	12.28	3.51	17.54
		capacity (mm)	560	590	600	capacity (m ³)	3050	2850	3100
	Green	norm diff.	54.05	59.46	62.16	norm diff.	22.81	14.04	24.56
		capacity (mm)	370	390	380	capacity (m ³)	2450	2450	2450
		norm diff.	2.70	5.41	2.70	norm diff.	1.75	0.00	1.75

- The impact of **UKCP09 sample ensemble uncertainty** compared with other investigated uncertainties was **larger** at **dry sites** (Brooms Barn and Woburn)

and **smaller** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Laplace**.

- The impact of **UKCP09 sample ensemble uncertainty** compared with other investigated uncertainties was **larger** at **dry sites** (Brooms Barn and Woburn) and **smaller** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Maximin**.
- The impact of **UKCP09 sample ensemble uncertainty** compared with other investigated uncertainties was **equal** at **dry sites** (Brooms barn and Woburn) and **larger** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Maximax**.
- The impact of **UKCP09 sample ensemble uncertainty** compared with other investigated uncertainties was **equal** at **dry sites** and **larger** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Minimax regret**.
- The impact of **UKCP09 sample ensemble uncertainty** compared with other investigated uncertainties was **equal** at **dry sites** and **larger** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Hurwicz**.
- The impact of **UKCP09 sample ensemble uncertainty** compared with other investigated uncertainties was **larger** at **dry sites** and **smaller** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using the **Green Z-score**.

8.4.3 11SCP uncertainty summary

Table 8.3 Normalised relative impact score (0-100) attributable to 11SCP uncertainty and decision outcome of irrigation reservoirs (mm) and SUDS (m³) (pond shown) for the site of Brooms Barn. Results obtained using 10,000 sample ensemble change factor dataset and a median “most likely” decision outcome from economic analysis. Results for Slaidburn and Woburn are shown in Table F-3.

Decision criteria	Emission	Irrigation reservoir – Brooms Barn			SUDS (pond) – Brooms Barn		
		Probabilistic projections	11SCP	norm diff.	Probabilistic projections	11SCP	norm diff.
Laplace	Low	390	350	10.81	2500	2150	12.28
	Med	410	350	16.22	2450	2450	0.00
	High	400	360	10.81	2500	2500	0.00
Maximin	Low	0	300	81.08	1500	2150	22.81
	Med	0	300	81.08	1900	2500	21.05
	High	0	300	81.08	1600	2550	33.33
Maximax	Low	600	370	62.16	3800	3000	28.07
	Med	620	370	67.57	3600	3400	7.02
	High	650	370	75.68	4000	3450	19.30
Minimax regret	Low	420	350	18.92	2750	2500	8.77
	Med	450	350	27.03	2550	2800	8.77
	High	430	350	21.62	2900	2850	1.75
Hurwicz	Low	560	370	51.35	3050	2150	31.58
	Med	590	370	59.46	2850	2900	1.75
	High	600	370	62.16	3100	2800	10.53

- The impact of **11SCP uncertainty** compared with other investigated uncertainties was **generally larger** at **dry sites** (Brooms Barn and Woburn) and **smaller** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Laplace**.
- The impact of **11SCP uncertainty** compared with other investigated uncertainties was **larger** at **dry sites** (Brooms Barn and Woburn) and **smaller** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Maximin**.
- The impact **11SCP uncertainty** compared with other investigated uncertainties was **larger** at **all sites** when designing irrigation reservoirs compared with SUDS when using **Maximax**.

- The impact of **11SCP uncertainty** compared with other investigated uncertainties was **larger** at **all sites** when designing irrigation reservoirs compared with SUDS when using **Minimax regret**.
- The impact of **11SCP uncertainty** compared with other investigated uncertainties was **equal** at **dry sites** and **larger** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Hurwicz**.

8.4.4 Sub-sampling uncertainty (using different sampling methods) summary

Table 8.4 Normalised relative impact score (0-100) attributable to sub-sampling uncertainty (using different sampling methods) and decision outcome of irrigation reservoirs (mm) and SUDS (m3) (pond shown) for the site of Brooms Barn. Results obtained using 10,000 sample ensemble change factor dataset and a median “most likely” decision outcome from economic analysis. Results for Slaidburn and Woburn are shown in Table F-4.

Decision criteria	Emission	Irrigation reservoir – Brooms Barn					SUDS (pond) – Brooms Barn				
		Decision outcome					Decision outcome				
		Complete dataset		SRS	OPT LHS	MAX LHS	Complete dataset		SRS	OPT LHS	MAX LHS
Laplace	Low	390	capacity (mm)	390	380	390	2500	capacity (m ³)	2450	2500	2480
			norm diff.	0.00	2.70	0.00		norm diff.	1.75	0.00	0.70
	Med	410	capacity (mm)	400	400	400	2450	capacity (m ³)	2450	2450	2450
			norm diff.	2.70	2.70	2.70		norm diff.	0.00	0.00	0.00
	High	400	capacity (mm)	400	400	400	2500	capacity (m ³)	2450	2500	2450
			norm diff.	0.00	0.00	0.00		norm diff.	1.75	0.00	1.75
Maximin	Low	0	capacity (mm)	250	250	240	1500	capacity (m ³)	2000	2000	2000
			norm diff.	67.57	67.57	64.86		norm diff.	17.54	17.54	17.54
	Med	0	capacity (mm)	280	260	260	1900	capacity (m ³)	2000	2000	1950
			norm diff.	75.68	70.27	70.27		norm diff.	3.51	3.51	1.75
	High	0	capacity (mm)	240	250	240	1600	capacity (m ³)	2000	2000	2000
			norm diff.	64.86	67.57	64.86		norm diff.	14.04	14.04	14.04

		Irrigation reservoir – Brooms Barn					SUDS (pond) – Brooms Barn				
		Decision outcome					Decision outcome				
Maximax	Low	600	capacity (mm)	510	480	500	3800	capacity (m ³)	3050	3130	3130
			norm diff.	24.32	32.43	27.03		norm diff.	26.32	23.51	23.51
	Med	620	capacity (mm)	500	510	520	3600	capacity (m ³)	2930	2900	2900
			norm diff.	32.43	29.73	27.03		norm diff.	23.51	24.56	24.56
	High	650	capacity (mm)	520	540	530	4000	capacity (m ³)	3150	3130	3080
			norm diff.	35.14	29.73	32.43		norm diff.	29.82	30.53	32.28
Minimax regret	Low	420	capacity (mm)	410	400	400	2750	capacity (m ³)	2600	2580	2600
			norm diff.	2.70	5.41	5.41		norm diff.	5.26	5.96	5.26
	Medium	450	capacity (mm)	410	420	420	2550	capacity (m ³)	2450	2450	2450
			norm diff.	10.81	8.11	8.11		norm diff.	3.51	3.51	3.51
	High	430	capacity (mm)	410	430	420	2900	capacity (m ³)	2550	2550	2550
			norm diff.	5.41	0.00	2.70		norm diff.	12.28	12.28	12.28
Hurwicz	Low	560	capacity (mm)	460	440	460	3050	capacity (m ³)	2700	2750	2730
			norm diff.	27.03	32.43	27.03		norm diff.	12.28	10.53	11.23
	Medium	590	capacity (mm)	470	470	480	2850	capacity (m ³)	2530	2500	2500
			norm diff.	32.43	32.43	29.73		norm diff.	11.23	12.28	12.28
	High	600	capacity (mm)	480	500	490	3100	capacity (m ³)	2700	2650	2680
			norm diff.	32.43	27.03	29.73		norm diff.	14.04	15.79	14.74
Green	Low	370	capacity (mm)	370	370	370	2450	capacity (m ³)	2480	2500	2500
			norm diff.	0.00	0.00	0.00		norm diff.	1.05	1.75	1.75
	Medium	390	capacity (mm)	380	390	380	2450	capacity (m ³)	2450	2500	2500
			norm diff.	2.70	0.00	2.70		norm diff.	0.00	1.75	1.75
	High	380	capacity (mm)	380	380	380	2450	capacity (m ³)	2480	2500	2450
			norm diff.	0.00	0.00	0.00		norm diff.	1.05	1.75	0.00

- The impact of **sub-sampling uncertainty (using different sampling methods)** compared with other investigated uncertainties was **generally equal** at **dry sites** (Brooms Barn and Woburn) and **generally smaller** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Laplace**.
- The impact of **sub-sampling uncertainty (using different sampling methods)** compared with other investigated uncertainties was **generally**

larger at **dry sites** (Brooms Barn and Woburn) and **smaller** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Maximin**.

- The impact of **sub-sampling uncertainty (using different sampling methods)** compared with other investigated uncertainties was **generally equal** at **dry sites** (Brooms Barn and Woburn) and **larger** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Maximax**.
- The impact **sub-sampling uncertainty (using different sampling methods)** compared with other investigated uncertainties was **generally equal** at **dry sites** and **larger** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Minimax regret**.
- The impact of **sub-sampling uncertainty (using different sampling methods)** compared with other investigated uncertainties was **equal** at **dry sites** and **larger** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Hurwicz**.
- The impact of **sub-sampling uncertainty (using different sampling methods)** compared with other investigated uncertainties was **generally smaller** at **dry sites** and **generally smaller** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using the **Green Z-score**.

8.4.5 Downscaling uncertainty summary

Table 8.5 Normalised relative impact score (0-100) attributable to downscaling uncertainty and decision outcome of irrigation reservoirs (mm) and SUDS (m3) (pond shown) for the site of Brooms Barn. Results obtained using 10,000 sample ensemble change factor dataset and a median “most likely” decision outcome from economic analysis. Results for Slaidburn and Woburn are shown in Table F-5.

Decision criteria	Emission	Irrigation reservoir – Brooms Barn			SUDS (pond) – Brooms Barn		
		Change factor	Weather generator	norm diff.	Change factor	Weather generator	norm diff.
Laplace	Low	390	350	10.81	2500	2850	12.28
	Med	410	360	13.51	2450	2800	12.28
	High	400	370	8.11	2500	2850	12.28
Maximin	Low	0	0	0.00	1500	2000	17.54
	Med	0	0	0.00	1900	1500	14.04
	High	0	0	0.00	1600	1500	3.51
Maximax	Low	600	570	8.11	3800	4600	28.07
	Med	620	520	27.03	3600	5800	77.19
	High	650	560	24.32	4000	6050	71.93
Minimax regret	Low	420	440	5.41	2750	3750	35.09
	Med	450	430	5.41	2550	3750	42.11
	High	430	450	5.41	2900	4300	49.12
Hurwicz	Low	560	550	2.70	3050	4350	45.61
	Med	590	490	27.03	2850	3900	36.84
	High	600	540	16.22	3100	5500	84.21
Green	Low	390	340	13.51	2500	2750	8.77
	Med	410	350	16.22	2450	2750	10.53
	High	400	360	10.81	2500	2750	8.77

- The impact of **downscaling uncertainty** compared with other investigated uncertainties was **generally equal** at **dry sites** (Brooms Barn and Woburn) and **generally smaller** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Laplace**.
- The impact of **downscaling uncertainty** compared with other investigated uncertainties was **generally smaller** at **dry sites** (Brooms Barn and Woburn) and **smaller** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Maximin**.

- The impact of **downscaling uncertainty** compared with other investigated uncertainties was **generally equal** at **dry sites** (Brooms Barn and Woburn) and **smaller** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Maximax**.
- The impact of **downscaling uncertainty** compared with other investigated uncertainties was **generally smaller** at **dry sites** and **generally equal** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Minimax regret**.
- The impact of **downscaling uncertainty** compared with other investigated uncertainties was **smaller** at **dry sites** and **smaller** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using **Hurwicz**.
- The impact of **downscaling uncertainty** compared with other investigated uncertainties was **larger** at **dry sites** and **smaller** at **wet sites** (Slaidburn) when designing irrigation reservoirs compared with SUDS when using the **Green Z-score**.

8.4.6 Overall summary

Table 8.6 Average normalised relative impact (NRI) attributable to different sources of uncertainty of irrigation reservoirs and SUDS (pond shown) for dry sites at Brooms Barn and Woburn and a wet site at Slaidburn.

Decision criteria	Case study	Impact Site	Average Normalised Relative Impact (NRI)				
			Low	Low-Medium	Medium	Medium-High	High
Laplace	Irrigation reservoir	Dry	1) Sampling 1.05	2) Emission 4.50	3) Downscaling 8.11	4) Sample ensemble 10.36	5) 11SCP 18.92
		Wet	1) Emission, Sample ensemble, 11SCP, Sampling, Downscaling 0				
	SUDS	Dry	1) Sampling 0.66	2) Emission 2.34	3) Sample ensemble 4.97	4) Downscaling 6.73	5) 11SCP 9.36
		Wet	1) Sampling 0.82	3) 11SCP, Sample ensemble 3.51		4) Emission 5.85	5) Downscaling 6.43
Maximin	Irrigation reservoir	Dry	1)Emission, Downscaling 0		3) Sampling 34.08	4) 11SCP 74.32	5) Sample ensemble 94.59
		Wet	1) Emission, Sample ensemble, 11SCP, Sampling, Downscaling 0				
	SUDS	Dry	1) Emission 4.68	2) Downscaling 5.85	3) Sampling 10.53	4) 11SCP 12.87	5) Sample ensemble 21.05
		Wet	1) Emission 3.51	11SCP 4.68	4) Sampling 9.55	5) Sample ensemble, Downscaling 25.73	
Maximax		Dry	1) Emission	2) Downscaling	3) Sampling	4) Sample ensemble	5) 11SCP

Decision criteria	Case study	Impact Site	Average Normalised Relative Impact (NRI)				
			Low	Low-Medium	Medium	Medium-High	High
	Irrigation reservoir	Wet	12.61	18.47	29.13	67.57	71.17
			1) Emission, Downscaling		3) Sampling	4) 11SCP	5) Sample ensemble
	SUDS	Dry	9.01		21.02	47.75	82.88
			1) Emission	2) Sampling	3) Downscaling	4) 11SCP	5) Sample ensemble
		Wet	11.11	30.27	37.72	54.68	68.71
			1) 11SCP	2) Sampling	3) Emission	4) Downscaling	5) Sample ensemble
			7.60	11.46	19.88	36.84	38.60
Minimax regret	Irrigation reservoir	Dry	1) Downscaling	2) Sampling	3) Emission	4) Sample ensemble	5) 11SCP
			4.95	6.16	8.11	19.82	28.83
	SUDS	Wet	1) Downscaling	2) Emission	5) Sample ensemble, 11SCP, Sampling		
			4.95	8.11	32.43		
		Dry	1) Emission	2) Sampling	3) Downscaling	4) Sample ensemble	5) 11SCP
			7.60	14.70	26.61	28.07	30.12
		Wet	1) 11SCP, Downscaling		3) Sampling	4) Emission scenario	5) Sample ensemble
			5.26		6.51	11.70	14.04
Hurwicz	Irrigation reservoir	Dry	1) Emission	2) Downscaling	3) Sampling	4) Sample ensemble	5) 11SCP
			9.01	12.16	29.58	57.21	63.06
		Wet	1) Emission, Downscaling		5) Sample ensemble, 11SCP, Sampling		
			5.41		78.38		
	SUDS	Dry	1) Emission	2) Sampling	3) Downscaling	4) Sample ensemble	5) 11SCP
			6.43	31.01	47.95	51.46	51.75

Decision criteria	Case study	Impact Site	Average Normalised Relative Impact (NRI)				
			Low	Low-Medium	Medium	Medium-High	High
Green	Irrigation reservoir	Wet	1) Sampling	2) 11SCP	3) Emission	4) Sample ensemble	5) Downscaling
			9.36	14.62	16.37	22.22	24.56
		Dry	N/A	2) Sampling	3) Emission	4) Sample ensemble	5) Downscaling
			N/A	0.45	4.50	4.95	11.71
		Wet	N/A	Emission, Sample ensemble, Sampling, Downscaling			
			N/A	0			
	SUDS	Dry	N/A	2) Emission	3) Sampling	4) Sample ensemble	5) Downscaling
			N/A	2.34	2.65	2.92	5.56
		Wet	N/A	1) Sampling	3) Sample ensemble	4) Emission	5) Downscaling
			N/A	1.01	2.92	5.85	7.02

- When using **Laplace**
 - For the purpose of designing **irrigation reservoirs**, the results suggest that **11SCP uncertainty** had the **largest impact** and **sampling uncertainty** had the **smallest impact** at **dry sites (Brooms Barn and Woburn)**, whereas **all sources of uncertainty** had an **equal impact** at **wet sites (Slaidburn)**.
 - For the purpose of designing **SUDS**, the results suggest that **11SCP uncertainty** had the **largest impact** and **sampling uncertainty** had the **smallest impact** at **dry sites (Brooms Barn and Woburn)**, whereas **downscaling uncertainty** had the **largest impact** and **sampling uncertainty** had the **smallest impact** at **wet sites (Slaidburn)**.
- When using **Maximin**
 - For the purpose of designing **irrigation reservoirs**, the results suggest that **UKCP09 sample ensemble uncertainty** had the **largest impact** and **emission scenario and downscaling uncertainty** had the **smallest impact** at **dry sites (Brooms Barn and Woburn)**, whereas **all sources of uncertainty** had an **equal impact** at **wet sites (Slaidburn)**.
 - For the purpose of designing **SUDS**, the results suggest that **UKCP09 sample ensemble** had the **largest impact** and **emission scenario uncertainty** had the **smallest impact** at **dry sites (Brooms Barn and Woburn)**, whereas **sample ensemble and downscaling uncertainty** had the **largest impact** and **emission scenario uncertainty** had the **smallest impact** at **wet sites (Slaidburn)**.
- When using **Maximax**
 - For the purpose of designing **irrigation reservoirs**, the results suggest that **11SCP uncertainty** had the **largest impact** and **emission scenario uncertainty** had the **smallest impact** at **dry sites (Brooms Barn and Woburn)**, whereas **UKCP09 sample ensemble uncertainty** had the **largest impact** and **emission and downscaling uncertainty** had the **smallest impact** at **wet sites (Slaidburn)**.
 - For the purpose of designing **SUDS**, the results suggest that **UKCP09 sample ensemble** had the **largest impact** and **emission scenario**

uncertainty had the **smallest impact** at **dry sites (Brooms Barn and Woburn)**, whereas **UKCP09 sample ensemble uncertainty** had the **largest impact** and **11SCP uncertainty** had the **smallest impact** at **wet sites (Slaidburn)**.

- When using **Minimax regret**
 - For the purpose of designing **irrigation reservoirs**, the results suggest that **11SCP uncertainty** had the **largest impact** and **downscaling uncertainty** had the **smallest impact** at **dry sites (Brooms Barn and Woburn)**, whereas **UKCP09 sample ensemble, 11SCP and sampling uncertainty** had the **largest impact** and **downscaling uncertainty** had the **smallest impact** at **wet sites (Slaidburn)**.
 - For the purpose of designing **SUDS**, the results suggest that **11SCP uncertainty** had the **largest impact** and **emission scenario uncertainty** had the **smallest impact** at **dry sites (Brooms Barn and Woburn)**, whereas **UKCP09 sample ensemble uncertainty** had the **largest impact** and **11SCP and downscaling uncertainty** had the **smallest impact** at **wet sites (Slaidburn)**.
- When using **Hurwicz**
 - For the purpose of designing **irrigation reservoirs**, the results suggest that **11SCP uncertainty** had the **largest impact** and **emission scenario uncertainty** had the **smallest impact** at **dry sites (Brooms Barn and Woburn)**, whereas **UCKP09 sample ensemble, 11SCP and sampling uncertainty** had the **largest impact** and **emission and downscaling uncertainty** had the **smallest impact** at **wet sites (Slaidburn)**.
 - For the purpose of designing **SUDS**, the results suggest that **11SCP uncertainty** had the **largest impact** and **emission scenario uncertainty** had the **smallest impact** at **dry sites (Brooms Barn and Woburn)**, whereas **downscaling uncertainty** had the **largest impact** and **sampling uncertainty** had the **smallest impact** at **wet sites (Slaidburn)**.
- When using the **Green Z-score**

- For the purpose of designing **irrigation reservoirs**, the results suggest that **downscaling** had the **largest impact** and **sampling uncertainty** had the **smallest impact** at **dry sites (Brooms Barn and Woburn)**, whereas **all sources of uncertainty** had an **equal impact** at **wet sites (Slaidburn)**.
- For the purpose of designing **SUDS**, the results suggest that **downscaling uncertainty** had the **largest impact** and **emission scenario uncertainty** had the **smallest impact** at **dry sites (Brooms Barn and Woburn)**, whereas **downscaling uncertainty** had the **largest impact** and **sampling** had the **smallest impact** at **wet sites (Slaidburn)**.
- Hence:
 - For the purpose of designing **irrigation reservoirs**, **Laplace** and the **Green Z-score** were **least affected** and **Maximax** and **Hurwicz** were **most affected** by the sources of uncertainty considered by this research.
 - For the purpose of designing **SUDS**, **Laplace** and the **Green Z-score** were **least affected** and **Maximax** and **Hurwicz** were **most affected** by the sources of uncertainty considered by this research.

8.5 Discussions

Decision makers are very familiar with the concept of risk, however it is only recently that they have begun to acknowledge the importance of uncertainty and methods for dealing with it (Andrews et al., 2004). When faced with uncertainty, there is a tendency among decision makers for inaction, who prefer to “wait and see” as opposed to taking action which may later prove to be wrong and costly to rectify (Tykocinski and Pittman, 1998; Skinner et al., 2013). However such action or more accurately lack of action can have significant consequences and should not be considered an appropriate response, given the apparent failure of mitigation efforts, which themselves will take some time before their full effects are felt.

Placing more emphasis on using multiple sources of climate change information to ensure decisions are robust to climate change uncertainty is one way to mitigate potential impacts associated with future climate change, akin to the concept of robust decision making, which focuses on identifying strategies that are immune to a wide range of uncertainties, instead of a “predict and optimise” approach (Dessai et al., 2009; Wilby and Dessai, 2010; Lempert and Groves, 2010). It is this field of decision making that the Green Z-score has sought to emulate.

In terms of recorded differences between wet and dry sites and irrigation reservoirs and SUDS, the following noticeable differences were recorded. When using Laplace to inform irrigation reservoirs at both dry and wet sites all of the sources of uncertainty considered generally had a small impact on the decision outcome. However, despite the small impact, a clear distinction is apparent between dry and wet sites. The results suggest that at wet sites irrigation reservoirs are rarely needed as there is generally sufficient water for rain-fed irrigation. As a result the differences caused by the investigated uncertainties are generally negligible as inaction is generally a more favourable outcome. In terms of designing SUDS no noticeable distinction can be made between dry and wet sites, although when compared with irrigation reservoirs, downscaling uncertainty had a much larger impact.

When using Maximin to inform reservoir, a clear distinction is apparent between dry and wet sites, similarly to using Laplace, wet sites favoured inaction regardless of the uncertainties. However at dry sites, very large differences were recorded, such when moving from the complete sample ensemble to a single “most likely” projection or the 11SCP. This result can be similarly attributed to the low irrigation demand at Slaidburn and the large impact of the sample ensemble uncertainty to the design of irrigation reservoirs at dry sites. Emission scenario and downscaling uncertainty, similarly to wet sites, had a negligible impact on the decision outcome. For the purpose of designing SUDS, all the uncertainties had a similar impact on decision making, although the impact of uncertainties when using Maximin were generally larger than when using Laplace, suggesting that Laplace results in decision outcomes that are theoretically more robust, because the outcomes are less sensitive to the uncertainties.

When using Maximax to inform irrigation reservoirs, dry and wet sites were reasonably similar in terms of the sensitivity of the decision outcomes to the investigated uncertainties. SUDS on the other hand showed very large differences between dry and wet sites in terms of the sensitivities of the decision outcomes. Dry sites were generally more sensitive when compared with wet sites. This result would suggest that the economic performance of SUDS at dry sites, where water is more plentiful, are very sensitive to uncertainty or more accurately the inclusion of extremely wet years when using the best case scenario to inform SUDS design.

For the purpose of informing reservoir capacity using Minimax regret, dry and wet sites were reasonably similar in terms of their sensitivity to the investigated uncertainties with the exception of sampling which had a larger impact at dry sites. In terms of SUDS, all of the investigated uncertainties with the exception of emission scenarios which had a much larger impact at dry sites than at wet sites.

For the purpose of designing irrigation reservoirs using Hurwicz, dry and wet sites were reasonably similar in terms of their sensitivity to the investigated uncertainties, although sampling had a much larger impact at wet sites. In terms of SUDS, the investigated uncertainties had a much larger impact at dry sites

compared with wet sites. For the purpose of designing irrigation reservoirs and SUDS, all of the investigated uncertainties had a negligible impact on the decision outcome.

This research considered only a proportion of known sources of uncertainty. Beginning with the choice of time slice, a selection of these uncertainties and those directly included in the analysis here are provided in Table 8.7. Each source of uncertainty may differ in its source, level and nature, but all will have an impact on the decision outcomes, the significance of which will depend on the particular decision problem and the options under consideration. Unfortunately, the impact of each would need to be confirmed by individual analysis.

Table 8.7 Sources of uncertainty

Uncertainty		Irrigation reservoir	SUDS
Time slice	2020s		
	2030s		
	2040s		
	2050s	X	X
	2060s		
	2070s		
	2080s		
Emission scenario	Low A1F1	X	X
	Medium A1B	X	X
	High B1	X	X
UKCP09	Sample ensemble	X	X
	11SCP	X	X
Downscaling	Change factor	X	X
	UKCP09 Weather generator	X	X
	Other		
Evapotranspiration	Penman-Monteith	X	X
	Hargreaves		
	Other		
Sampling	SRS	X	X

	Optimum LHS	X	X
	Maximin LHS	X	X
	Other		
WaSim	Soil type	X	X
	Crop type		
	Irrigation schedule		
Urban runoff	Site parameters		
	Runoff parameters		
Assets	Irrigation reservoirs		X
	SUDS	X	
	Other		
Unit cost	CAPEX		
	OPEX		
	Benefit		
Discount rate	3.5%	X	X
	Other		
Decision maker	Risk appetite	X	X

X – Investigated uncertainty

A criticism levelled against probabilistic projections used here is that the probability assigned to an outcome may be mistakenly construed as the probability of that outcome in reality. However, it is merely the probability of the outcome in the modelled results (Beven, 2011). It has been suggested that in order to increase the effectiveness of UK water resource management in the future we need to move towards risk-based approaches (Hall et al., 2012). Central to risk-based approaches, is the idea of a pre-defined Level of Service (LoS), such as a drought warning curve at a particular reservoir. The determination of an appropriate LoS is vitally important and equally as challenging. For example, there is little merit in investing in adaptation measures which would completely eradicate the possibility of a system failure. However, once set it is believed that a LoS would not change significantly over time, but instead would require gradual investment over time to adjust to threats from climate change. The range of projections provided by UKCP09 can be transformed into

a distribution of probabilities of failing to meet a particular LoS each year for a designated time slice or the probability of a particular system failing in the future (Harris et al., 2012). However, without proper communication, such an approach may inadvertently lead to the same issues highlighted by Beven, (2011). By prescribing a “probability” to an outcome, whether that is the projection or the probability of failing to meet a particular LoS of the probability of that outcome in the modelled results, we may inadvertently lead decision makers to believe we know more about the probability of an outcome in reality than we actually do. As a result, the Green Z-score was carefully designed to remove all notion of probability from the description and computation of the criterion, instead all projections are treated and described as equi-likely, acknowledging the current view that we cannot realistically quantify the real-world probability of an outcome occurring.

8.6 Conclusions

It is the conclusions of this chapter that different sources of uncertainty can have varying impacts on the decision making process. Generally speaking, the difference between using the complete sample ensemble and a median projection or the 11SCP had a very large impact on the decision outcome, evident by the large NRI recorded, whereas downscaling, emission scenario and sampling uncertainty generally had a small impact on the decision outcomes when using the vast majority of decision criteria with the investigated case studies. The results of this chapter show that the decision outcomes obtained using the Green Z-score and Laplace are among the least sensitive to the investigated uncertainties. On the basis of these results they can be considered to be more robust because the decision outcomes obtained using them were the most insensitive to uncertainties stemming from the sources considered by this research. In contrast, many of the other criteria that have previously been advocated for climate change adaptation were shown to be very sensitive to the investigated uncertainties and thus the decision outcomes obtained using them are likely to be less robust. However this result is very much based on the definition of robustness that is used. Two distinct definitions of robustness have

previously been introduced 1) dynamic robustness and 2) static robustness. Static robustness is aimed at reducing vulnerability in the largest possible range of outcomes whereas dynamic robustness or flexibility enables options to be changed as new information arises (Lemos and Morehouse, 2005; Reeder and Ranger, 2011). Practical examples of dynamic robustness have yet to be realised in any significant capacity in practice, which suggests that decision making is still undertaken as a linear approach, despite its negative connotations among the scientific community (Tang and Dessai, 2012). On the basis static robustness, Laplace and the Green Z-score proved the most successful, evident by their insensitivity to the investigated uncertainties. The benefit of the latter is that it enables the risk appetite of the decision maker to be engrained in the decision making process resulting in a transparent and analytically robust decision outcome.

CHAPTER 9. REFLECTIONS, CONCLUSIONS AND FUTURE WORK

9.1 Overview

A summary response to the original research question, limitations, novel contribution of this research and summary conclusions for each research objective is provided. Areas of further work are also summarised.

9.2 Reflections

9.2.1 Research Question and Response

A summary response to the original research question ‘what are the advantages, disadvantages and implications of using probabilistic projections for decision making for adaptation planning for local water management in the UK?’ is provided below.

The advantages of having access to probabilistic projections of the future climate are numerous and from the perspective of knowledge producers i.e. individuals involved in the preparation or delivery of climate change information very clear. Probabilistic projections are much more transparent when it comes to communicating the uncertainty associated with modelling the future climate. It is already acknowledged that the future climate is beset by uncertainty and this is unlikely to change in the future, indeed uncertainty may even grow in the future as we begin to better understand natural processes. Providing decision makers with a range of possible projections as opposed to a single definitive value represents a big step forward towards a more risk-based decision making framework and provided they are used correctly can lead to more robust decision outcomes. It is increasingly accepted that continuing to provide deterministic point forecasts of the future climate is absurd, especially for a system with such complex systems as the Earth’s climate (Frigg et al., 2013).

UKCP09, unlike previous iterations, also provide a number of other benefits including supplying higher resolution climate change projections i.e. 25 km² instead of 50 km² as well as projections for predefined aggregated regions such

as administrative regions, river basins and certain marine regions. Compared with previous iterations of the UK climate projections, UKCP09 offers much greater functionality, enabling the projections to be visualised in a number of different ways including maps, graphs or as numerical data, the latter of which was used exclusively here. UKCP09 is perceived to be both credible and legitimate. It is its perceived credibility with regulators in the UK as opposed to its scientific reputation which makes it particularly attractive to decision makers (Tang and Dessai, 2012). The advantage of using probabilistic projections, even if they do not consider or communicate all of the uncertainties is that organisations using them are still safeguarded from the most extreme socio-political criticisms, whether this justifies their use is a contentious issue. Indeed, by ensuring they use an array of projections and not just a single deterministic projection which may later prove to be wrong decision makers can effectively minimize their institutional exposure. UKCP09 blends both a perturbed physics ensemble and a multi-model ensemble, use of the latter has been shown to provide a more skilful representation of the present-day climate compared with using any one member of a multi-model ensemble, although it is acknowledged that all climate models are subject to systematic errors (Frigg et al., 2013).

UKCP09 was originally designed to provide a common framework for assessing the impact of future climate change, but paradoxically because of its lack of saliency it may not actually provide a common platform. The probabilities underpinning the UKCP09 probabilistic projections are not without their controversy, as the type of probabilities used by them, i.e. Bayesian, is less familiar to decision makers who are more accustomed and familiar with using frequentist probabilities. Bayesian probabilities are less favoured by decision makers because of difficulties applying them in practice. Probabilistic projections, like those from UKCP09, “assign a probability to different possible climate change outcomes recognizing that ... giving a range of possible climate change outcomes is better, and can help with making robust adaptation decisions, but would be of limited use if we could not say which outcomes are more or less likely than others” (Jenkins, 2009, p. 23).

Concerns have been raised about the climate models underpinning UKCP09, themselves subject to systematic errors, as the basis for probabilistic forecasts. The projections provided by them can be misleading as the probability of an event within a projection ensemble is not the same as the probability of that event in reality (Stainforth et al., 2007; Hall, 2007). Probabilistic forecasts have been viewed as unreliable and as a result do not provide a good basis for action (Frigg et al., 2013). Concerns have been raised not about the width of the uncertainty distribution described by the projections being too narrow but the distribution being entirely in the wrong place and the median of that distribution being entirely different to the actual future in reality (Frigg et al., 2013).

An extreme reaction to the unreliability of climate models might be to just dispose of them, given the uncertainty of the forecasts that they ultimately produce. However, this sort of action has been equated to “throwing out the baby with the bathwater” as in the short term models can be incredibly useful, even in the medium term in about 30% of cases models can model future conditions with reasonable certainty (Frigg et al., 2013). Some have questioned how far into the future can we provide accurate and reliable projections of the future climate, something that is only really known with hindsight. Stakeholders should seek to find a healthy balance between the useful insights models provide and the issues that may arise if they are found to be incorrect in the future (Frigg et al., 2013). The use of non-probability odds has been suggested previously (Frigg et al., 2013), although clearly more research is needed to find ways of using this information for decision support. Indeed, it has already been suggested that climate models are currently unable to provide the kind of information that current decision making frameworks require. Solutions may not be found in improving climate models but it is the opinion of this author that maybe more effort should be directed at developing decision frameworks that can take this inherent uncertainty into account (Hallegatte, 2009).

The UK Government and on behalf of the Devolved Administrations of Scotland, Wales and Northern Ireland have continued to fund projects to create climate change projections since 1991. In the UK, we are now in our fifth generation of

national climate projections; this is because decision makers often need to address issues arising at the local scale, such as when designing flood barriers that need to be built in a particular location or have a sufficient height. In these situations, having access to local user-relevant information about future climate change impacts is incredibly useful, provided that this information does not later prove to be misinformation (Smith and Stern, 2011). Factories, such as those producing components for the latest mobile phones have a lifetime of a few decades (Hallegatte, 2009). It is highly unlikely, that these kinds of assets will be placed at significant risk of climate change impacts ensuring they have not been constructed on floodplains or along the coast. There are however many assets and decisions with long term commitments that may be impacted in direct/indirect ways and which may be incredibly sensitive to the prevailing climate. Examples include urbanisation plans, risk management strategies, building design, transportation and infrastructure development for water management, the latter of which is the focus of this research. These type of decisions have consequences over periods of 50-200 years and reasonably justify the use of the 2050s time slice seen here (Hallegatte, 2009).

In terms of the implications for local water management, the research found that use of probabilistic projections for decision making had varied implications depending on the site in question and severity of extreme outcomes included in the analysis. Generally speaking, the assets considered here were insensitive to the use of probabilistic projections except in situations where a polarised decision criterion was used, such as Maximin and Maximax. Decision outcomes obtained using these decision criteria were found to be incredibly sensitive to the inclusion of a small proportion of the probabilistic ensemble (in the region of 5% of the projections). Removing these projections from the analysis, such as when taking sub-samples of the probabilistic ensemble, had a large impact on the decision outcome as these decision criteria use only the extreme projections from the probabilistic ensemble and not the complete dataset.

The results of this research raise a number of interesting points of discussion. For a simple decision problem, involving just one stakeholder or a number of

stakeholders with common objectives and/or asset performance measures which are insensitive to the climate, the impact of using probabilistic projections instead of deterministic projections are likely to be small. For example, irrigation reservoirs typically have only one interested stakeholder, that being the farmer seeking to build the reservoir and they will usually only be interested in the economic return on their investment. While some may argue that other stakeholders may benefit from constructing irrigation reservoirs such as those sectors competing for water resources e.g. industry, they are unlikely to be directly involved in the decision making process. Furthermore, given the insensitivity of the performance measure used here i.e. NPV of irrigation reservoirs and SUDS to climate change, it is not surprising that using the complete probabilistic ensemble versus some sub-sample of the ensemble had a fairly low impact on the decision outcomes when using neutral decision criteria like Laplace, but much greater impacts when using polarised decision criteria like Maximin and Maximax. The implications of using probabilistic projections for decision problems, where multiple stakeholder are concerned can have significant implications, provided these stakeholders weight performance measures differently and at least one of these measures is sensitive to the prevailing climate. Of course if these performance measures can be integrated and the resulting composite performance measure is insensitive to the prevailing climate then the impact of probabilistic projections will likely remain small.

The case studies presented through this research were both insensitive to climate change. This result may be partially attributed to the common climate variable i.e. precipitation which was used to inform their design. Interestingly, the difference between the current period and the 2050s in terms of the annual precipitation is relatively small and this may partially account for the observed insensitivity. It should be remembered that more uncertainty simply means that a broader set of possible future states of the world need to be “considered and integrated” (Patt and Weber, 2013), decision makers should where possible avoid using just a single projection from the probabilistic ensemble. Provided this extra uncertainty is integrated into existing decision frameworks, then the implications of probabilistic projections will likely remain small. New decision frameworks

continue to be developed, yet based on research of existing decision criteria, some of which have been around for several decades the use of the complete probabilistic ensemble, with all of the uncertainty it considers had a comparably small impact. This result is consistent for the case studies presented here, whether the same is true for other assets in the water sector is of course open to discussion and is a recommended area of further research.

9.2.2 Limitations

A great deal of debate hinges on the selection of an appropriate discount rate to apply to future costs, especially where benefits will be felt by future populations and largely measured by changes in future consumption, future threats to humanity and changes in consumption patterns and preferences for market and non-market goods (Patt and Weber, 2013). There is indeed strong theoretical arguments for using declining discount rates for projects with a long life term and this is reflected in the government policies of France, Norway, US and the UK, the latter of which was used here. The reality is that we know much less about the future state of the world and uncertainty in general than these widely accepted discount rates would have us believe (Freeman and Groom, 2013).

With regards to social discount rates there are generally two camps of thought, the first believe that future populations and present populations value capital equally, the second, which this research prescribes to, is that the social discount rate should “reflect the informed preferences in people in general”, as is the norm in cost benefit analysis” (Spackman, 2011, p. 28). A wider review of the scientific literature found that a discount rate of 1.5% and higher in some cases was reasonably justified. Here a value of 3.5% was used based on current government guidelines and the author maintains that this is justified (Treasury, 2003). Instead of debating the appropriateness of different discount rates, we accept it is a limitation and valid source of uncertainty in our analysis. However as shown by sensitivity analysis, its impact was somewhat negligible and should not detract from the findings of this research. Further limitations may include the use of just three sites or the particular case studies used, although the author maintains that sufficient justification of these design decisions is provided in the

earlier chapters of this thesis. Of course, had more time been made available, additional sites and case studies may have been explored, although it is the authors opinion that their absence should not detract from the findings of this research or our ability to answer the proposed research question.

Uncertainty associated with future emission scenarios cannot, at least at present, be described in probabilistic terms. As a result it should be acknowledged that the reliance on a limited number of just three emission scenarios to describe the magnitude and range of future emission scenarios is an acknowledged limitation of this research. UKCP09 is a subject of continuing debate and discussion, while some maintain it is a credible and legitimate source of climate change information, others question the scientific validity and appropriateness of the methods employed by it. It is not entirely unreasonable to approach climate science with a fair degree of scepticism, given the often controversial and significant implications it may have for humanity as a whole. Indeed this scepticism and continual often heated debate has in part empowered the scientific community to delve deeper into the uncertainties and make climate science as a whole much more transparent in recent years. Recently, much of the work in the climate science community has focused on dispelling misinformation and findings new and innovative ways to address and communicate the uncertainty. The inherent uncertainty in the future climate far from detracting from the value of the science should serve to highlight the usefulness of novel decision frameworks aimed at bridging the gap between the climate science community and stakeholders engaged in adaptation such as those presented here.

9.2.3 Contribution

In conclusion, the novel contributions of this research to the topic area are once again highlighted:

1. **A quantitative understanding of the impact and sensitivity of uncertainty to decision making for adaptation planning for local water management** was obtained from a literature review; followed by a comparison of using (1) the low, medium and high emission scenarios, (2)

10,000 sample ensemble and 11SCP, (3) deterministic and probabilistic climate change projections, (4) the complete probabilistic dataset and subsamples of it (using different sampling techniques), (5) the change factor (delta change) and stochastic (UKCP09 weather generator) downscaling techniques and (6) different decision criteria for two distinct and contrasting case studies at three UK sites.

2. **A novel decision criterion and accompanying framework to support adaptation planning** was developed to identify robust decision outcomes in situations of uncertainty “in which analysts do not know or the parties to a decision cannot agree upon (1) the appropriate models to describe interactions among a system’s variables, (2) the probability distributions to represent uncertainty about key parameters in the models, and/or (3) how to value the desirability of alternative outcomes” (Walker et al., 2013, p.958).

9.3 Conclusions

Conclusions are summarised with regards to the intended objectives of this research.

Objective 1 Explore how stakeholders can use probabilistic projections to support climate change adaptation planning and explore current motivation and uptake barriers to adaptation.

Stakeholders can use probabilistic projections in a variety of different ways to help inform climate change adaptation, not least the methods considered here. In ensuring they inform robust decision outcomes stakeholders should utilise a large range of projections and identify decisions which (1) provide acceptable outcomes for a large proportion, if not all of the states of nature, (2) exhibit sufficient flexibility so that they can be altered as new information arises or (3) are insensitive to the prevailing uncertainties. Stakeholders should avoid using individual “deterministic” projections of the future climate and this includes using the 50th percentile or similar quartile from a probabilistic ensemble. Relying on individual projections, which may later prove to be wrong if the probabilistic distribution and the median of that distribution are found to be entirely in the

wrong place, can lead to maladaptation and ultimately loss of confidence in the stakeholder undertaking the adaptation and the knowledge produce, in this example the climate science community.

Motivation for using probabilistic projections is driven largely by the greater transparency they offer in terms of uncertainty associated with modelling the future climate. Stakeholders are beginning to acknowledge the extent of the uncertainty in the future climate, although uptake has been slow and has not been helped by the release of UKCP09, which some may argue was too soon for it to be of any real use to decision makers. Barriers to adaptation are numerous and can arise due to difficulties or an inability due to different mental models to detect/accept the existence of a definitive climate signal or problem, lack of availability and accessibility to data and its saliency and credibility. In addition, barriers often manifest themselves during the implementation of options, typically these are the result of resource constraints e.g. fiscal, technical etc., legality and procedural feasibility and willingness to learn and revisit previous decisions.

Objective 2 Critically evaluate current methods of using probabilistic projections for climate change adaptation planning with a focus on local water management.

A variety of methods of using probabilistic projections for climate change adaptation planning were explored including methods of downscaling, sub-sampling and the use of different decision criteria, details of which are provided below.

Sub-objective 2.1 Critically compare scenario-led and vulnerability-led approaches to climate change adaptation.

Scenario-led and vulnerability led approaches to climate change adaptation come with advantages and disadvantages. Generally speaking, both approaches can be viewed as complimentary as opposed to mutually exclusive, as exemplified by the hybrid approaches that have emerged recently within the scientific literature. Scenario-led approaches enable climate change impacts to be assessed well into the future, facilitating the evaluation of alternative adaptation strategies against

the backdrop of climate uncertainty. In terms of the weaknesses of scenario-led adaptation, considerable effort and time must be invested in training user communities to establish the most appropriate tools and methods to use to inform adaptation given the vast uncertainties associated with peering so far into the future. Indeed it should be stressed that while models are subject to considerable uncertainties in terms of the deep future, in the short term and even in the medium term models have proved incredibly useful. With regards to vulnerability-led adaptation, the main advantage is that it removes the need for climate change scenarios, a potential source of uncertainty, as well as lengthy observations. However, while useful for assessing the vulnerability of human communities, there is a danger that extreme events in the local media can be over or under-reported. Bottom-up approaches provide legitimacy through stakeholder involvement; however unlike top-down approach they tend to give insufficient attention to physical factors and uncertainties.

Sub-objective 2.2 Critically compare the 11SCP and the 10,000 sample ensemble datasets. Establish whether these datasets would yield different decision outcomes and explore the implications of using probabilistic projections in place of non-probabilistic (deterministic) projections.

The fundamental difference between these two datasets is the range of uncertainty considered by them. The 11SCP projections are not probabilistic in nature and so do not replicate the breadth of uncertainty considered by the UKCP09 sample ensemble. Each dataset comes with their own advantages and disadvantages and far from repeating these, we will focus on their implications for the case studies considered here. Despite the additional uncertainty considered by it, use of the probabilistic ensemble instead of the 11SCP generally had a small impact on the decision outcome, except where certain polarised decision criteria were used. This would suggest that the bulk of the probabilistic projections and 11SCP were reasonably in agreement with regards to the implied course of action, at least for the purpose of irrigation reservoir and SUDS design. Indeed, unless the decision maker was particularly optimistic or pessimistic about

the future, the same course of action would likely result regardless of which dataset was used. While Laplace is a very old decision criterion, its use can still be seen in modern decision frameworks including Environment Agency, (2013). The results of this research seem to suggest that these decision frameworks and other using Laplace as their basis, will likely result in similar outcomes regardless of what dataset is used. Far from suggesting that the 11SCP should replace the probabilistic ensemble, these results would suggest that Laplace is an exceptionally robust decision criterion, able to robust decision outcomes which are insensitive to investigated uncertainties.

Sub-objective 2.3 Establish whether sub-sampling the probabilistic projections is appropriate, establish whether different decision outcomes would arise if sub samples were used in place of the complete dataset and explore the implications of using advanced stratified sampling methods (LHS) over simple random sampling methods.

The result of this research suggests that using fewer than the 100 projections stipulated by UKCIP, provided certain decision criteria are avoided, does not dramatically impact the decision outcome. Increasing the sample size is obviously more beneficial provided it does not complicate the decision making process. Decision makers should select an appropriate sample size that best represents a balance between sampling accuracy and efficiency. A small sample size was purposely used here to establish what implications it would have for decision making. Interestingly, consistent with the other sources of uncertainty explored by this research, its impact was relatively small, except where exceptionally polarised decision criteria were used. These polarised decision criteria, such as Maximin and Maximax proved very difficult to reproduce from small sub-samples, even when using more advanced sampling methods. This can similarly be attributed to the small samples sizes used and the small proportion of the probabilistic ensemble which result in exceptionally extreme decision outcomes. Interestingly, both simple random and advanced stratified

sampling methods produced similar decision outcomes regardless of the site and decision criteria used. This result could be attributed to the small sample sizes used and the apparent weak correlation between the climate variables which were used to construct the sub-samples and the economic performance measures by which the options were assessed.

Sub-objective 2.4 Critically compare the change factor (delta factor) and stochastic (UKCP09 weather generator) downscaling techniques. Establish whether these downscaling techniques would yield different decision outcomes to each other and explore the implications of using one approach over the other.

The advantages and disadvantages of different downscaling methods including the change factor and weather generator approach is an area of science that is well trodden, indeed many of the articles cited by this research cover these and other downscaling procedures in much greater detail. Still few researchers have attempted to assess the implications of this and other sources of uncertainty on the impact of decisions in quantitative terms. Generally speaking the impact of downscaling on the decision outcome was small when compared with the other investigated uncertainties. In terms of irrigation reservoir design, choice of downscaling procedure had a somewhat negligible impact, regardless of the decision criteria used. This result can be largely attributed to the methods used to calculate the irrigation demand deficit and thus estimate the size of irrigation reservoir required. SUDS on the other hand were much more sensitive, although this was only really apparent when using exceptionally polarised decision criteria at certain sites. In some cases, the impact of changing the downscaling procedure had a comparable impact as changing the emission scenario. It is the conclusions of this research, that while downscaling can dramatically reshape day to day climate variability, in terms of asset design it generally has a low impact as these type of assets are typically assessed over much longer time periods where a lot of this variable information is aggregated to produce annual estimates.

Sub objective 2.5 Critically compare decision criteria using probabilistic climate projections for adaptation planning, establish whether these criteria would yield different decision outcomes to each other and explore the implications of using one approach over the other.

The decision outcomes obtained using the decision criteria shown here were generally found to be insensitive to the use of probabilistic projections and not highly variable, with the exception of certain polarised decision criteria including Maximin and Maximax. The irrigation reservoir and SUDS capacities calculated using these two criteria were found to be incredibly sensitive to the inclusion of some extreme probabilistic projections and not the complete dataset. A small proportion of the probabilistic projections, in the region of 5% had the largest impact. These projections are likely the result of a small number of members from the multimodel ensemble, although it is not possible to say which members were responsible for these outcomes and why these members produced such radically different results as this information is obscured from the analyst by UKCP09. The findings of this research support the view that decision makers should avoid where possible using polarised decision criteria such as Maximin, Maximax and Hurwicz when seeking to inform robust adaptation strategies. These sort of decision criteria typically only use one projection, or two in the case of Hurwicz to identify the most appropriate course of action, whether that is the best case scenario or the worst case scenario. Such decision criteria are unlikely to result in the most robust decision outcomes, especially if these extreme projections are later proved to be wrong. Use of such criteria can also be incredibly expensive, as the decision outcomes obtained using them tend to be entirely impractical from a cost perspective. Even where they have been implemented on the basis of UKCP09, use of these criteria does not protect against “black swans”, as only partial quantification of the uncertainties could be achieved by the creation of the probabilistic projections. Minimax regret, which continues to be used to help resolve decision problems in situations of uncertainty, was found to be more sensitive to the investigated uncertainties compared with Laplace suggesting that

it is less suitable to identifying robust decision outcomes, on the basis of the case studies shown here, despite its popular appeal.

Objective 3 Develop recommendations and improved methods for using probabilistic projections for climate change adaptation planning.

The final and potentially most important objective of this research was to develop recommendations and improved methods for using probabilistic projections for climate change adaptation planning. Far from surprising, many of the recommendations that were identified after undertaking detailed CBA already exist in some capacity or another, and some are relatively well known to stakeholders involved in the preparation and delivery of climate change adaptation strategies. Here robustness can be defined as insensitivity to uncertainty. On this basis, Maximin and Maximax have shown to be the least robust of the investigated decision criteria in terms of the identified adaptation strategies. Laplace on the other hand is acknowledged to be the most robust of the investigated decision criteria, as shown by the insensitivity of the decision outcomes identified using it. It should be remembered that Laplace is not without its limitations and criticisms; it is unable to accommodate different risk appetites due to its inflexibility. As a result the Green Z-score was developed to bypass a number of these limitations while still assisting in the identification of robust adaptation strategies. The Green Z-score (Green and Weatherhead, 2014c) is a novel decision criterion which can be used to inform robust adaptation strategies in situations of “deep” uncertainty. Adaptation strategies identified using the Green Z-score have been shown to be exceptionally robust and highly reproducible from small sub-samples of the UKCP09 dataset. The purpose of the Green Z-score was to “bridge the gap between the science of UKCP09 and its user base” and in this sense it was highly successful. It places the focus on the choice behaviour, enabling individuals to resolve trade-offs in a transparent, audible and analytically robust manner. Enabling individuals to rapidly see how their perception of climate change and uncertainty translates into action on the ground, while simultaneously facilitating the evaluation of different sources of uncertainty on decision making. Most importantly the criterion was designed to

be flexible, meaning it can be applied to a range of different case studies and problems and was not constrained to a single application, a limitation of existing methods.

9.4 Future Work

The case studies explored by this research have specifically focussed on irrigation reservoirs and SUDS design. However, the findings of this research can provide a robust means by which to assess the impacts of future climate change and prepare appropriate adaptation strategies for other assets. A number of other potential avenues for further research have also been identified.

Firstly, this research evaluated the impact of emission scenario uncertainty in only a limited capacity; this is because we currently do not have access to probabilistic emission scenarios. In the future, these might become available and it would be interesting to see what impact they have compared to the other investigated uncertainties shown here. In addition, model structure and technical uncertainty stemming from the WaSim model was only explored in a limited capacity, further analysis could explore what impact varying these sources of uncertainty had compared with the much larger uncertainties associated with the probabilistic projections. Other sources of uncertainty highlighted by this research could also be included in this analysis. This combined results of this much larger study could be used to evaluate whether uncertainties stemming from climate change projections had a more significant impact on real-world decisions compared with existing uncertainties (e.g. discount rate) that are already considered by decision makers.

Secondly, the Green Z-score was developed with scenario-led adaptation in mind, as would a decision maker choosing to use UKCP09 to gauge the impacts of future climate change. It is increasingly accepted that hybrid approaches blending both top-down and bottom-up approaches are preferred to conventional scenario-led or bottom-up approaches. Future work might thus focus on developing the Green Z-score criterion described here into a more comprehensive framework of alternatively integrating it with existing decision methods such as Real Option Analysis or RDM. Of course this would require

considerable effort and is beyond the scope of this PhD although it remains a valid course of action for future research.

Thirdly, further research could focus on developing the Green Z-score into a web-based methodological toolkit. By collecting Meta data on its usage and user base, this tool could provide valuable insight into the different risk appetites and approaches to managing uncertainty adopted by decision makers. For example, the tool may reveal that a significant proportion of the user-base are inherently risk seeking or risk adverse when faced with a particular decision problem. A range of different hypothetical problems could be provided, including entirely different assets, subtle variations of assets considered by this research or assets in entirely different sectors (e.g. marine renewables, forestry etc.).

Finally, future research may look to evaluate the impact of different decision methods, not criteria, on decision making, while methods such as Info-Gap theory and RDM were discussed here in a limited capacity, a more comprehensive review of these against the other sources of investigated uncertainties shown here is recommended. Again, this is beyond the scope of this research, though the results of which would help to inform the debate on the most robust methods for undertaking climate change adaptation. The author is personally aware that such comparisons are already underway, but have so far excluded many of the sources of uncertainties shown here.

9.5 Policy Recommendations

A series of policy recommendations were produced from the key findings of this research:

1. Encourage and support collaboration between scientists and decision makers

Scientists and decision makers need to work together to address future problems and uncertainties. In order to do so they must understand the needs, capabilities and limitations of each other, without which such collaborations will likely fail or result in outcomes that are not accommodating of the different values and beliefs of the diverse actors involved. Such collaborations could take the form of knowledge transfer partnerships, joint research and development projects, co-

publications or the creation of appropriate funding schemes to support collaboration activities and research.

2. Create regional centres of adaptation expertise.

Additional funding should be provided to create regional centres of adaptation expertise. Comprised of representatives from the scientific, public and private sector communities, these clusters could work together to identify suitable funding opportunities and highlight priority areas for action. Working together, these clusters, will develop new ways of thinking, encourage decision makers to ask the difficult questions and encourage scientists to consider the wider impact of their research on real world decisions, thereby bridging the gap between scientific theory and practice reality.

3. Provide training and tools to scientists and decision makers

Scientists need to better understand how decision makers make decisions and what information they need, decision makers must understand what uncertainty is and what impact it could have on their assets. New tools will need to be developed to bridge the gap between scientists and decision makers, such tools should be analytically robust and easily transferable across different sectors and stakeholder groups. These tools will need to “translate” the information provided by scientists into a format that is amenable with decision making and vice versa.

4. Support leadership and innovation

Leadership and innovation are both essential to adaptation to climate change, technological and institutional innovations can increase resilience and lessen the severity of impacts of future climate change. Leadership will be fundamental in mainstreaming adaptation, without which adaptation will continue to occur in isolation and could potentially lead to maladaptation, if system linkages and feedbacks are not explicitly considered by individual actors.

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APPENDICES

Appendix A HR Wallingford SUDS storage estimation

Table A-1 HR Wallingford SUDS storage estimation methodology and results

Site	Brooms Barn	Slaidburn	Woburn
Reference	u123kctj3qj3	gcw70sh5xn0g	gcpxfmp01t2r
Latitude	52.26015° N	53.98745° N	52.01480° N
Longitude	0.56723° E	2.43317° W	0.59457° W
Site characteristics			
Total site area (ha)	10	10	10
Significant public open space	0	0	0
Area positively drained	10	10	10
Impermeable area	8	8	8
Percentage of drained area that is impermeable	80	80	80
Impervious area drained via infiltration	0	0	0
Return period for infiltration system design	10	10	10
Impervious area drained to rainwater harvesting systems	0	0	0
Return period for rainwater harvesting system design	10	10	10
Compliance factor for rainwater harvesting system design	66	66	66
Net site area for storage volume design	10	10	10
Methodology			
Greenfield runoff method	IH124		
Volume control approach	Use Long Term Storage		
Qbar estimation method	Calculate from SPR and SAAR		
SPR estimation method	Calculate from SOIL type		
SOIL type	1	4	4

HOST class	N/A	N/A	N/A
SPR	0.10	0.47	0.47
SAAR (mm)	580	1527	634
M5-60 Rainfall Depth (mm)	20	20	20
'r' Ratio M5-60/M5-2 day	0.4	0.2	0.4
FEH/FSR conversion factor	0.88	0.87	0.87
Hydrological region	5	10	5
Growth curve factor: 1 year	0.87	0.87	0.87
Growth curve factor: 10 year	1.65	1.38	1.65
Growth curve factor: 30 year	2.45	1.7	2.45
Growth curve factor: 100 year	3.56	2.08	3.56
Design criteria			
Climate change allowance factor	1	1	1
Urban creep allowance factor	1	1	1
Interception rainfall depth (mm)	5	5	5
Greenfield runoff rates			
Qbar (l/s)	1.35	120.25	43
1 in 1 year (l/s)	8.7	104.62	37.41
1 in 30 year (l/s)	24.50	204.42	105.34
1 in 100 year (l/s)	35.60	250.12	153.07
Estimated storage volumes			
Interception storage (m3)	320.00	320.00	320.00
Attenuation storage	1769.51	1880.99	2487.56
Long term storage	3402.00	1394.00	1071.00
Treatment storage	960.00	960	960.00
Total storage	5491.51	3594.99	3878.56

Appendix B Coping with climate change uncertainty for adaptation planning an improved criterion for decision making under uncertainty using UKCP09

Climate Risk Management

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Coping with climate change uncertainty for adaptation planning: an improved criterion for decision making under uncertainty using UKCP09

Abstract

Despite information on the benefits of climate change adaptation planning being widely available and well documented, in the UK at least relatively few real-world cases of scenario led adaptation have been documented. This limited uptake has been attributed to a variety of factors including the vast uncertainties faced, a lack of resources and potentially the absence of probabilities assigned to current climate change projections, thereby hampering conventional approaches to decision making under risk. Decision criteria for problems of uncertainty have been criticised for being too restrictive, crude, overly pessimistic, and data intensive. Furthermore, many cannot be reproduced reliably from sub-samples of the UKCP09 probabilistic dataset.

This study critically compares current decision criteria for problems of uncertainty and subsequently outlines an improved criterion which overcomes some of their limitations and criticisms. This criterion, termed the Green Z-score, is then applied to a simplified real-world problem of designing an irrigation reservoir in the UK under climate change. The criterion is designed to be simple to implement, support robust decision making and provide reproducible results from sub-samples of the UKCP09 probabilistic dataset. It is designed to accommodate a wide range of risk appetites and attitudes and thereby encourage its use by decision makers who are presently struggling to determine whether and how to adapt to future climate change and its potential impacts.

Analyses using sub-samples of the complete probabilistic dataset showed that the Green Z-score had comparable reproducibility to Laplace and improved reproducibility compared to other current decision criteria, and unlike Laplace is able to accommodate different risk attitudes.

Key words: Decision making, adaptation, uncertainty, UKCP09, WaSim, Green Z-score

Introduction

Despite information on the benefits of climate change adaptation planning being widely available and well documented, in the UK at least relatively few real-world cases of climate change adaptation planning have been recorded outside of government led initiatives (Tompkins et al., 2010). Elsewhere in the world, while adaptation has been recorded, it is generally limited to high income (developed) nations, has been viewed as inadequate and is seldom undertaken in response to climate change alone (Adger et al., 2009; Berrang-Ford et al., 2011; Chen et al., 2004). This limited uptake has been attributed to a variety of factors including the availability, accessibility and willingness to use information, availability of resources, leadership, legal and procedural feasibility and many more, see (Moser and Ekstrom, 2010) for a more comprehensive discussion.

Adaptation, like any decision problem, may be represented as a series of options, with different outcomes for each possible future state, amongst which a decision maker must choose the option which provides the “best” outcome (Tversky and Kahneman, 1986). Options can refer to both soft and hard solutions such as promoting education or building new infrastructure, outcomes refer to the payoff associated with these options and states refer to potential futures which may occur. Two distinct fields of decision theory are widely acknowledged (French, 1986), namely decision making under risk and decision making under uncertainty.

In the field of adaptation planning, decision makers often find themselves in situations of decision making under uncertainty “in which analysts do not know or the parties to a decision cannot agree upon (1) the appropriate models to describe interactions among a system’s variables, (2) the probability distributions to represent uncertainty about key parameters in the models, and/or (3) how to value the desirability of alternative outcomes” (Walker et al., 2013), p.958. A variety of decision criteria have been developed to address problems of decision making under uncertainty, discussions of which can be found here and in Chrisholm and Clark, (1993), Bouglet and Vergnaud, (2000) and more recently Ranger et al., (2010). In addition to several well-known decision criteria including

Laplace (Laplace and Simon, 1951), Maximin (Wald, 1945), Maximax, Hurwicz's criterion (Hurwicz, 1951) and Minimax regret (Savage, 1951), decision makers can generate problem-specific criteria using Multi-attribute utility theory (MAUT) or Multi-criteria analysis (MCA) (Dyer et al., 1992). MAUT and MCA consist of a wide range of methods, but in general the principle remains the same, options are compared using several criteria that are weighted to produce a single criterion. Alternatively, the criteria can be assigned a score and an aggregated score is then calculated. Any of these criteria can be used with existing robust decision methods for managing uncertainty, well-known examples of which include Info-gap theory (Ben-Haim, 2001; Ben-Haim, 2006), Robust decision making (Lempert and Groves, 2010) and Robust control optimization (Hansen and Sargent, 2008), introduced earlier, as well as Real option analyses (Amram and Kulatilaka, 1998). Here, criteria refer to the metrics used to compare options and identify the optimum decision outcome (typically by maximizing an objective function or satisficing constraints), whereas decision methods describe the steps by which these decision criteria are applied.

For the purpose of climate change adaptation planning, the vast majority of decision criteria rely on the decision maker having access to future climate change projections. One of the key sources of climate change projections in the UK is UKCP09 which provides probabilistic projections of future climate change (Murphy et al., 2011). The move from deterministic to probabilistic methods of communicating climate change information observed in recent years, driven by improvements in uncertainty quantification (Rougier, 2007; Stainforth et al., 2007; Tebaldi and Knutti, 2007) has further complicated the process of adaptation planning given that it communicates extra uncertainty within the projections that was previously not available to decision makers, who may have limited experience working with uncertainty (Green and Weatherhead, 2014d).

The scenarios used in this study are the SRES A1F1, A1B and B1 scenarios, referred to as the low medium and high greenhouse gas emission scenario within the current suite of national UK climate change projections (Nakicenovic and Swart, 2000). They represent different 'story lines', interweaving complex social,

economic and environmental factors (Polasky et al., 2011). All three scenarios, rather controversially, are often regarded as equi-probable (Harris et al., 2012). It has been argued that the vast uncertainties surrounding future climate change, more so in the distant future, make the prescription of probabilities unrealistic and an arguably subjective affair. Others have argued that the choice to not assign probabilities to either the original scenarios or the probabilistic projections provided by UKCP09 make the projections of limited value for decision making (Schneider, 2001; Schneider, 2006).

The large number of projections available within the UKCP09 probabilistic dataset, some 10,000 per emission scenario, may in some cases present a 'barrier to entry' for some decisions makers. A previous study by (Green and Weatherhead, 2014d) found that a number of decision criteria that are applied in situations of uncertainty have been shown to be incompatible with sub-samples of the probabilistic dataset. Decision criteria using a single projection to inform the decision outcome such as Maximin and Maximax have proved very difficult to obtain from small samples that are consistent with the complete probabilistic dataset (Green and Weatherhead, 2014d).

As a result of the large data requirements of decision methods under risk and the apparent limitations of some criteria for decision making under uncertainty, alternative decision criteria which are more compatible with the UKCP09 probabilistic climate change projections should be sought.

Aim

The aim of this study is to critically compare five current decision criteria and in turn develop a novel improved decision criterion, which supports robust decision making in situations of deep uncertainty. All five decision current criteria are evaluated using the full UKCP09 probabilistic ensemble and sub-samples of it to ensure the decision outcome associated with each could be reliably reproduced from sub-sampling. The novel decision criterion is initially described, it was designed to be simple to implement, support sensitivity analysis and be compatible with the UKCP09 probabilistic dataset and samples of it, to ensure it is suitable for real world decision making. The UKCP09 probabilistic dataset was

chosen owing to its legitimacy and credibility within the UK (Tang and Dessai, 2012), though the criterion presented in theory is applicable to all situations (and other countries) where multiple competing, though equally plausible, projections are available. If their probabilities are different but available, the decision maker can calculate an outcome for each state (by multiplying the probability of the state by the payoff), the best course of action can then be determined using any of the criteria shown here.

Material and methods

The methodology is presented in three stages; firstly five current decision criteria are described and their criticisms discussed. Secondly, an improved decision criterion is outlined. Thirdly, all of the decision criteria are applied to a simplified real-world problem of designing an irrigation reservoir to meet the water demands of a potato crop for the 2050s using climate change projections taken from UKCP09.

Current decision criteria

This study considered five decision criteria that are typically employed in situations of uncertainty, they include Laplace, Maximax, Maximin, Hurwicz's criterion and Minimax regret. Laplace is based on the principle of insufficient reason which assumes that all potential states are equi-probable in the absence of knowledge of event probability i.e. it assumes that there is no reason to favour one state over another. It identifies the best option as the option which yields the largest average expected outcome based on all the potential states. Maximin identifies the best option as the option which provides the largest expected outcome from the worst possible state. In contrast, Maximax identifies the best option as the option providing the largest outcome from the best possible state. The best option under Hurwicz's criterion is calculated using a weighted average of Maximin and Maximax (with the weighting defined by α , representing the optimism of the decision maker). Minimax regret identifies the option with the smallest regret, representing the difference between the best and worst possible outcomes across all states. Readers are directed to Ranger et al., (2010) for practical examples of applying these criteria.

A general criticism levelled against all of these criteria is that all are “rationalised on some notion of ignorance” (Froyn, 2005, p. 204). It has previously been suggested that none of the current decision criteria are as ‘good’ as one might wish (French, 1986). It seems highly unlikely that all five criteria (Laplace, Maximin, Maximax, Hurwicz and Minimax regret) are equal, and there must exist some way to evaluate which is best. This view led to the development of a set of axioms, which reflect ‘good’ properties of decision making criteria, and which may be used to formally assess which is optimal (French, 1986). If we accept the axiom basis of a criterion we should in theory accept its implications. However, none of the popular criteria are validated by all the axioms of decision theory and in fact it is not possible for any criterion to satisfy all of the axioms; see (French, 1986) for formal proof. As opposed to assessing our criterion against French’s original axioms of decision theory (French, 1986), we therefore explore the wider criticisms surrounding these criteria and examine whether or not they are suitable for use with the UKCP09 probabilistic climate change projections.

With regards to Laplace, two fundamental criticisms have emerged, namely that it is too restrictive in its design and that the principle of insufficient reason which states that all states are equally likely is “by no means as innocuous as it might appear” (French, 1986, p. 218). It has previously been suggested that it is rare (though not impossible) for no information to exist regarding the likelihood of states occurring, thus the premise of scenario symmetry (i.e. all scenarios are equally likely) is arguably flawed and with it the principle itself (Hajkowicz, 2008). Laplace was further criticised by Knight (Knight, 2012) who suggested that blind use of this approach can lead to absurd conclusions. Maximin and by extension Hurwicz’s criterion have been criticised for being too crude; Maximin in particular is considered to be overly pessimistic as an approach and not suitable for real world decision making (Etner et al., 2012). Minimax regret can be similarly criticised, the values of regret used to determine the optimal decision are not absolute but strictly relative, and as a result the decision outcome can be altered easily by introducing irrelevant or flippant options.

However, since we do not know the probability of the occurring event, it is reasonable to assume in situations of deep uncertainty that any projection is just as likely as any other. As a result, a core assumption of this study is that the probability distribution is considered to be uniform, akin to the ‘Laplacian’ view of decision making under uncertainty which is consistent with emerging guidelines (Environment Agency, 2013). While this may remain a point of contention for some individuals, the alternatives which would require us to generate subjective probabilities for each of the UKCP09 projections or omit projections that we perceive as unlikely is not advisable.

Current decision criteria, such as Maximax and Maximin, typically fit the decision maker to a specific rational model. In the case of Maximin, this rational model describes an individual that is particularly pessimistic, while Maximax describes an individual that is very optimistic. Laplace, in theory, represents a “neutral” viewpoint. A hypothetical problem, comparing three irrigation solutions, termed option A, B and C, across a discrete number of states is shown for demonstration. These options may represent entirely different solutions such as installing a new water delivery system or building an on-site reservoir. Alternatively, they may represent options which are subtly different such as building a lined or unlined reservoir. Figure B-1 was generated by ranking the outcome of three options from smallest to largest across a discrete number of states. In this (hypothetical) example, the average outcomes of options A, B and C happen to be equal. As such, Laplace would view these options as equal. Whilst there is nothing intrinsically wrong with this, real decision makers can and regularly do depart from this idealised sense of the rational decision maker. For example some optimistic decision makers may perceive option A to be the best because it could provide the largest outcome. Pessimistic decision makers may perceive option C to be the best because it has the smallest negative outcome. Other decision makers may prefer option B because it has a smaller number of states with a negative outcome.

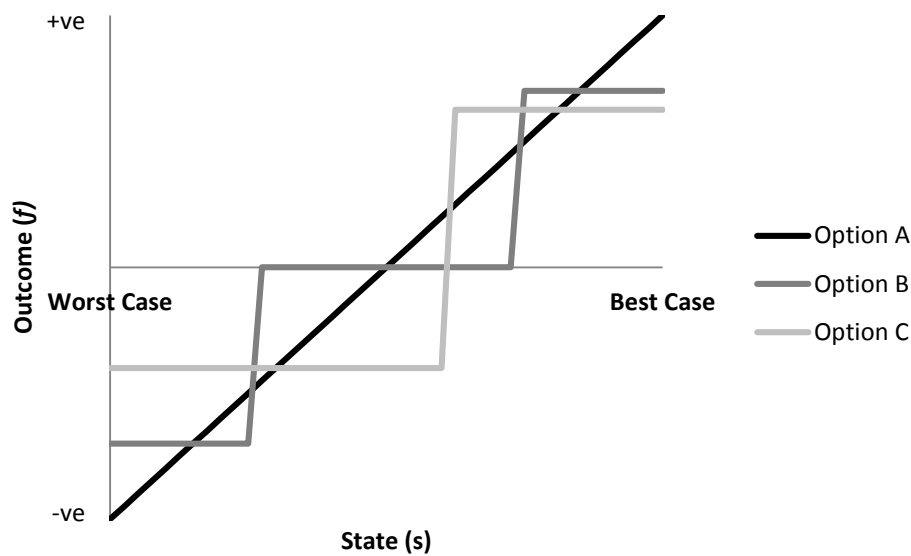


Figure B-1 Hypothetical problem comparing three options against a discrete number of states. Average outcome of option A, B and C are equal (not actual data).

Developing a novel decision criterion

Given the acknowledged limitations with the criteria discussed, an attempt has been made to develop a novel discussion criterion, hereby termed the Green Z-score, which considers all the potential options, outcomes and states, and hence is amenable to sub-sampling of the complete probabilistic dataset.

Unlike Laplace, which uses a single rational model to describe all decision makers, the Green Z-score uses three parameters to generate a simplified rational model that can be personalised to the individual decision maker, in many ways similar to MCA. MCA was selected as the basis for the Green Z-score as it places the focus on choice behaviour, enabling decision makers to resolve trade-offs in a transparent, audible and analytically robust manner (Hajkowicz, 2008). The parameters underpinning the Green Z-score consist of the coefficient of optimism (α), the coefficient of robustness (β), and a user defined threshold of acceptability (t), defining the boundary between acceptable and unacceptable outcomes. The coefficient of optimism is used to describe how optimistic the decision maker is about the future, specifically whether they are more concerned

about the negative or positive outcomes associated with a particular decision. The coefficient of robustness (β) is used to quantify how “robust” the decision maker wants their option to be, specifically whether they are more concerned about the overall performance of option across all states or merely those states where the option performs exceptionally better than all other options.

The Green Z-score for each option is calculated using a weighted difference between its overall performance, calculated across all states, and its negative performance, calculated across those states where the outcome falls below the threshold of acceptability. The weighting is determined by the coefficient of optimism α . The optimal decision outcome is then the option with the highest Green Z-score.

This concept of a coefficient of optimism (α) can be traced back to Hurwicz’s criterion which uses a similar criterion to describe how optimistic an individual is about the future. In Hurwicz’s weighted criterion model, the decision outcome is obtained using a weighted average of Maximin and Maximax, and hence only considers the payoffs from extreme states, which may not be considered in sub-samples of the complete probabilistic dataset. To calculate the Green Z-score, Maximin and Maximax in Hurwicz’s original model have been substituted with two alternative parameters. These parameters, termed the overall performance and negative performance respectively, are summed across all states, providing a value for each option.

The mathematical equation of the Green Z-score is shown below.

$$z_d = \max_{d \in D} \left((\alpha \cdot A) - ((1 - \alpha) \cdot B) \right)$$

Where:

z_d = decision outcome

d = option, D = options

α = coefficient of optimism (where $0 < \alpha \leq 1$)

A = overall performance

B = negative performance

$$A = \sum_{s=1}^{s=n} \left(\frac{(f_d - \chi)}{(\max_{d \in D} f_d - \chi)} \right)$$

Where:

f_d = option outcome

s = state

$$\chi = \left(\max_{d \in D} f_d - \left(\left(\max_{d \in D} f_d - \min_{d \in D} f_d \right) \cdot \left(\frac{\beta}{100} \right) \right) \right)$$

β = coefficient of robustness

$$B = \sum_{s=1}^{s=n} \left(\frac{(f_d - t)}{(\min_{d \in D} f_d - t)} \right)$$

Where:

f_d = option outcome

s = state

t = threshold of acceptability (e.g. 0)

Calculating the Green Z-score

The overall performance of each option is calculated first as follows. The effective outcome range of all options is calculated for each state. This is the difference between the maximum outcome and minimum outcome across all options, multiplied by the coefficient of robustness, $\beta/100$ (where $0 \leq \beta \leq 100$). This value is then deducted from the maximum outcome to calculate the minimum bound of the effective range. If absolute robustness is sought a β value of 100 is used, in which case the effective outcome range is the full 0-100% outcome range (i.e. max-min outcome for each state). If a β value of 50, say, is used, the effective outcome range is the 50-100% effective outcome range (i.e. max-median outcome for each state). The outcome of each option is then normalised against

the effective outcome range for each state. If the outcome of an option is equal to the maximum bound of the effective range for that state (i.e. it has the best outcome) it is assigned a value of 1. If the outcome of an option is equal to the minimum bound of the effective range for that state (i.e. it has the worst outcome), it is assigned a value of 0. Options in between are assigned a value of 0 to 1 depending on their position relative to the maximum outcome and minimum bound of the effective range. If the outcome of an option is less than the minimum bound (which can occur if $\beta < 100$) it is assigned a value of 0. The overall performance of each option is then obtained by summation across all states.

The negative performance of each option is then calculated for each state. The user defined threshold of acceptability (t) can be any value between the max and minimum outcome. Decision makers who are particularly risk adverse may use a high threshold, while those that are particularly risk seeking may use a low threshold. The acceptability range considering all available options is then calculated; this represents the difference between the threshold and the minimum outcome across all options. If the outcome of an option is less than this threshold then it is counted against the option's Green Z-score i.e. it is considered undesirable. The payoff of each option is then normalised against the acceptability range. If the outcome of an option is equal to the minimum bound of the acceptability range for that state (i.e. it has the worst outcome) it is assigned a value of 1. If the outcome of an option is equal to the maximum bound of the acceptability range for that state (i.e. it equals the threshold value), it is assigned a value of 0. Options in between are assigned a value of 0 to 1 depending on their position relative to the minimum bound and the maximum bound of the acceptability range. If the outcome of an option is greater than the maximum bound (which can occur if $t < \max f$) it is not counted towards the negative performance of that option. The negative performance of each option is then obtained by summation across all states.

The Green Z-score is then calculated by multiplying the overall performance by α (representing the coefficient of optimism) and deducting the negative

performance multiplied by $1-\alpha$. The option yielding the largest Green Z-score is then selected as optimal.

Applying the Green Z-score in practice

The Green Z-score is used to identify the optimal reservoir capacity at a number of sites distributed around the UK under climate change. Three sites representing different agro-climatic conditions are selected as case studies. Brooms Barn is located in the county of Suffolk, near Bury St Edmunds, approximately 30km east of Cambridge and is the driest of the investigated sites. Slaidburn is located in the district of Lancashire, approximately 60km north-west of Leeds and is the wettest site with an average annual rainfall of 1515 mm for the baseline period (1961-1990). Lastly, Woburn is situated in the county of Bedfordshire, 50km north-west of London and is marginally wetter than Brooms barn but with slightly lower annual evapotranspiration. Irrigation water requirements are calculated and used to inform the design of on-farm irrigation reservoirs using sequences derived from the full UKCP09 2050s 10,000 projection sample ensemble and sub-samples of it.

(Green and Weatherhead, 2014b) provide a detailed methodology covering the exact methods used to generate the future weather sequences used in this study. In summary, baseline observed climate data is extracted from a weather station at each site (Table B-1). All 10,000 monthly change factor climate change factors are extracted from the UKCP09 25km member ensemble for the 2050s time slice for a 25km grid square overlying each weather station (Figure B-2). Each set of monthly change factor is then used to perturb an observed baseline period daily weather series at each weather station to generate 10,000 future sequences for each site. This is repeated for all three emission scenarios, producing 90,000 climate projections in total (30,000 for each site, split across three emission scenarios).

Table B-1 Weather station sites and records used.

Station	Lat.	Long.	Elevation (m AOD)	Average annual (1961-1990)		Data	
				Rain (mm)	ETo (mm)	From	To
Brooms Barn	52.260	0.567	75	588	585	1964	1990
Slaidburn	53.987	-2.433	192	1515	487	1961	1990
Woburn	52.014	-0.595	89	632	564	1961	1990

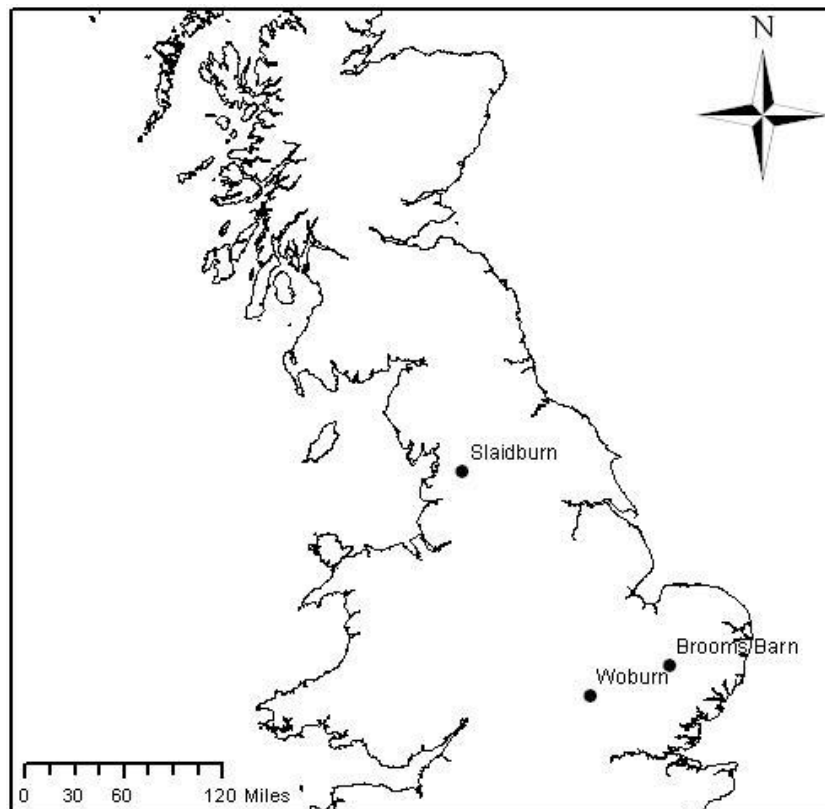


Figure B-2 Weather stations

WaSim is used to model the annual water use at each site. It simulates inflow (infiltration) and outflow (evapotranspiration and drainage) and storage of soil water in response to climate, irrigation and drainage. The annual water use of a potato crop is calculated for each year in the 10,000 x 30 year generated sequences for each site and emission scenario. Typical costs and benefits for clay agricultural reservoirs are obtained from a concurrent study (Green and Weatherhead, 2014b). Each of the future 10,000 projections is then used to calculate the net present value (NPV) of a range of reservoir sizes, with usable

storage capacities equivalent to applying from 0 to 1,000mm to the area irrigated (i.e. 0 to 10,000 m³.ha⁻¹). The Green Z-score is calculated for all reservoir capacities for all three sites and all three emission scenarios and the optimal reservoir capacity compared to those obtained using current decision criteria.

Results

With standard (neutral) parameter values, the optimal reservoir capacities from the Green Z-score and Laplace are largely similar. At all three sites the optimal reservoir capacity based on Green Z-score is within 25mm of Laplace, with the Green Z-score generally suggesting a slightly smaller capacity (Table B-2). Maximin typically results in no reservoir being built. Maximax results in much larger reservoir capacities compared to all other decision criteria. The range within each decision outcome (Table B-2) highlights the considerable uncertainty in the probabilistic dataset while the difference between the criteria reflects the fundamental differences between them (Table B-2).

Table B-2 Optimum reservoir capacity (mm) obtained using a selection of current decision criteria for the three sites and three emission scenarios. Results obtained from 10,000 future projections for each emission scenario for each site. Each sequence generated from a perturbed observed series using monthly change factors taken from UKC09 10000 member ensemble 2050s time slice. Hurwicz calculated using $\alpha=0.5$. Green Z-score calculated using coefficient of robustness $\beta=100$, threshold of acceptability $t=0$, coefficient of optimism $\alpha=0.5$.

Site	Brooms Barn			Slaidburn			Woburn		
Emission scenario	L	M	H	L	M	H	L	M	H
Laplace	390	410	400	0	0	0	360	380	390
Maximin	0	0	0	0	0	0	0	0	0
Maximax	600	620	650	280	310	330	530	580	620
Minimax regret	420	450	430	100	120	140	380	420	440
Hurwicz	560	590	600	270	300	300	510	540	570
Green	370	390	380	0	0	0	340	360	370

Sensitivity to extreme projections

The optimal reservoir capacity associated with each decision criteria is subsequently compared using progressively fewer climate change projections, sequentially excluding the extreme outcomes. This is undertaken to establish how sensitive the optimal reservoir capacity associated with each decision criteria is to extreme projections within the probabilistic dataset and provide the basis for further analysis of sub-samples of the complete probabilistic dataset. This is achieved by first identifying the optimal reservoir capacity calculated using the complete probabilistic dataset i.e. all 10,000 projections, for each of the decision criteria. For each reservoir capacity, all 10,000 projections are then ranked in terms of NPV from smallest to largest. Projections are then systematically removed from the tail ends of the NPV distribution, re-calculating the optimal reservoir capacity after removing each projection, eventually leaving only the median projection.

The results for Woburn 2050s medium emission scenario are shown in Figure B-3. Similar results are obtained from the other sites and emission scenarios.

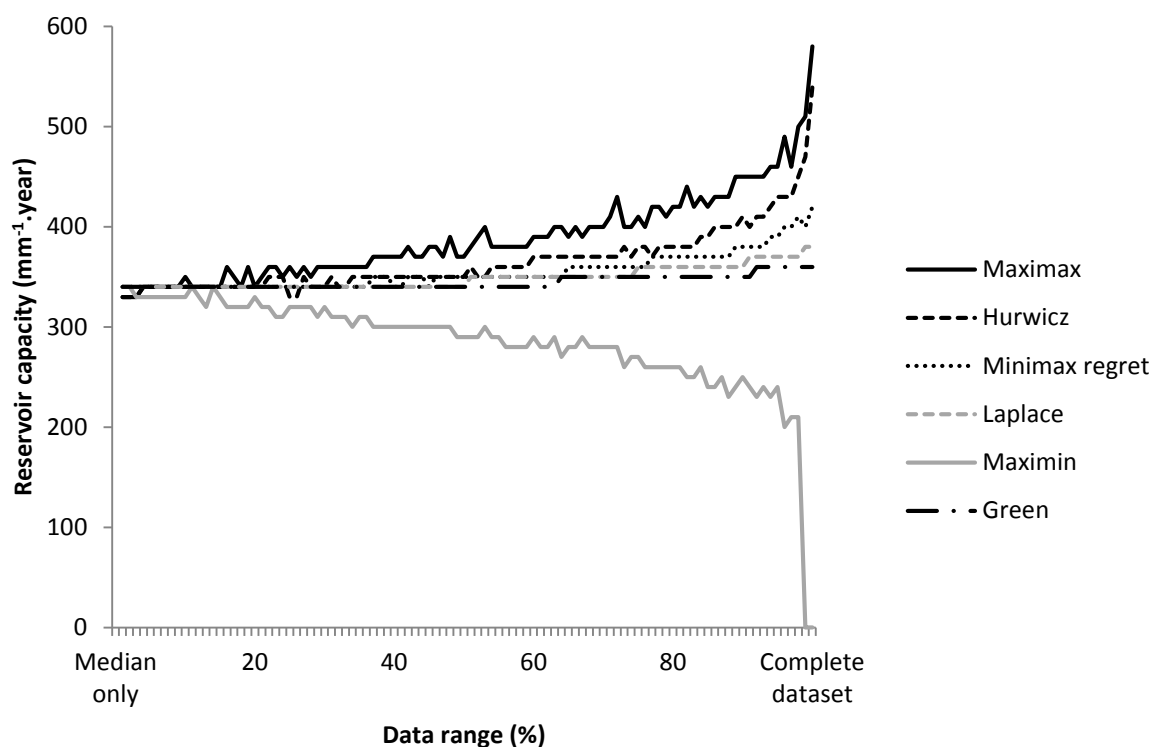


Figure B-3 Optimal reservoir capacities for various decision criteria generated excluding extreme climate change projections, for the 2050s medium emission scenario. Projections systematically removed in an iterative manner (right to left) starting with the most extreme (min and max NPV respectively), calculating the optimal reservoir capacity at each step. Hurwicz calculated using coefficient of optimism $\alpha=0.5$. Green Z-score calculated using coefficient of robustness $\beta=100$, threshold of acceptability $t=0$, coefficient of optimism $\alpha=0.5$. Adapted from (Green and Weatherhead, 2014d).

As a result of the complexity of many models, e.g. crop growth simulations, it is often not feasible to use all 10,000 projections, and therefore sampling is frequently used (Green and Weatherhead, 2014d) (alternatively, a rapid assessment model may be used, though readers are directed elsewhere for further details (Kwakkel et al., 2012; Haasnoot et al., 2012)). These sampling methods should be carefully designed to ensure they capture extreme projections so as not to bias the decision outcome should certain decision criteria be used. Combining a poorly designed sampling method with a decision criterion that is very sensitive to the inclusion of extreme projections such as Maximin or

Maximax can result in very different decision outcomes compared to using the complete probabilistic dataset (Green and Weatherhead, 2014d). Certain decision criteria are particularly sensitive, with clear trends emerging. Interestingly, Hurwicz tended to favour Maximax despite using a coefficient of optimism of 0.5. This result is the result of the number of “good” and “bad” projections contained within the complete probabilistic dataset, they are not equal and as such Hurwicz does not appear halfway between Maximax and Maximin. Beginning within the median projection from the probabilistic dataset and gradually introducing additional projections (Figure B-3), all six decision criteria are relatively stable up until 30%, beyond which they begin to diverge. Maximax and Maximin follow an exponential type curve, confirming that just a few extreme projections exert a substantial pull on the decision outcome. Maximax and Maximin each use a single extreme projection, best or worst, to inform the decision outcome and so this result is not unexpected. Laplace and Green Z-score are much less sensitive.

Due to the sensitive nature of Maximax and Maximin, and to a lesser extent Hurwicz and Minimax regret, use of these criteria with sub-samples of the complete UKCP09 probabilistic dataset can lead to misleading conclusions (Green and Weatherhead, 2014d). If, for example, the extreme projection is not sampled and thus excluded from the analysis, the result can be a very different sized reservoir.

Using sampled data with the Green Z-score

In order to establish whether the optimum reservoir capacity could be estimated from samples of the complete probabilistic dataset more reliably using the Green Z-score than using the current decision criteria, 30 simple random samples of 30 projections are extracted from the complete probabilistic dataset. The percentage difference between the optimum reservoir capacities obtained using each of the decision criteria with the complete probabilistic dataset and with each sample is calculated (Figure B-4). Simple random sampling was chosen both for convenience and on the basis of previous findings which suggest it provides

similarly rich sub-samples compared to more advance stratified methods (Green and Weatherhead, 2014d).

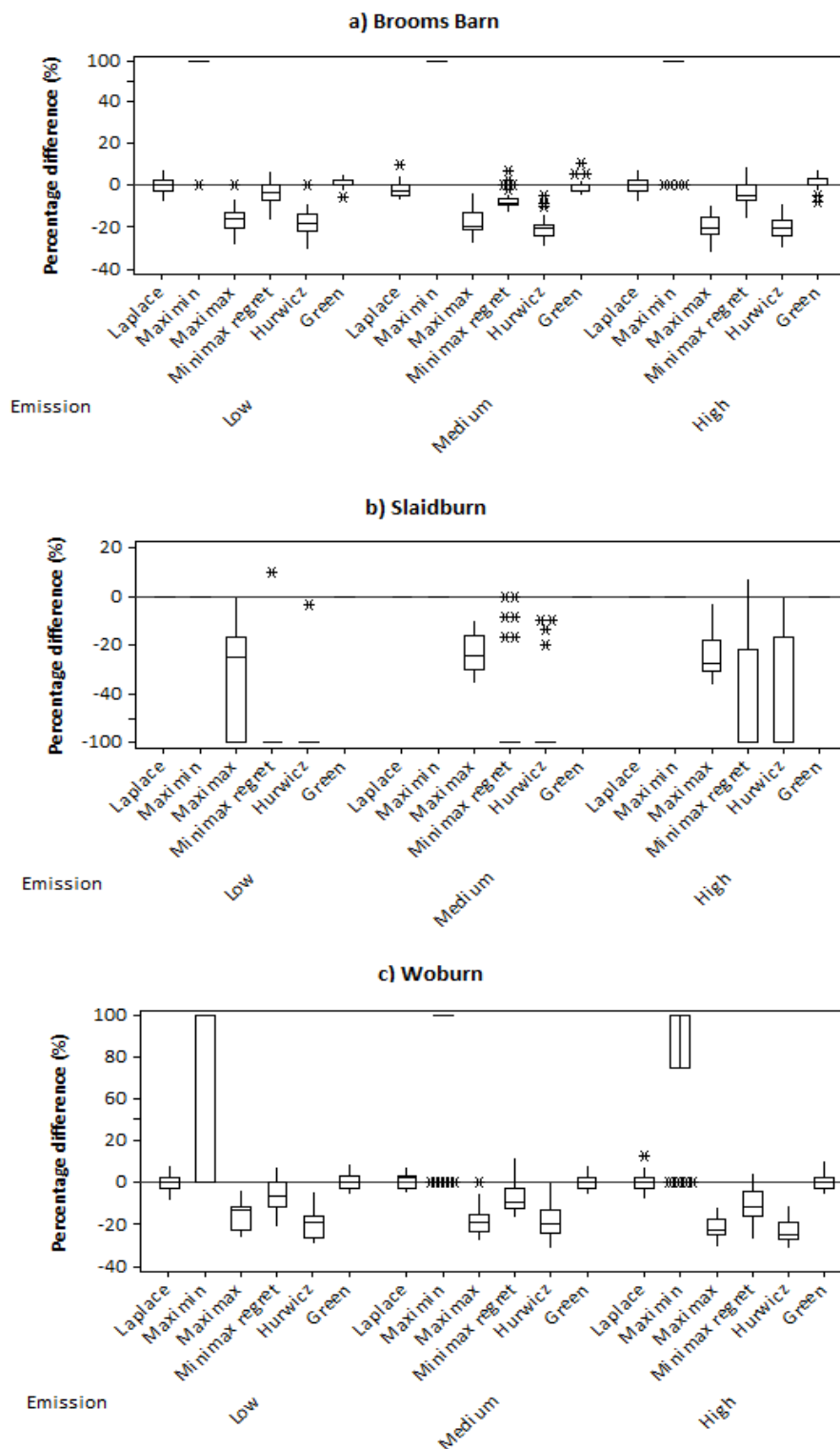


Figure B-4 Percentage difference in optimal reservoir capacity for each decision criteria using sub-samples of the probabilistic dataset in place of the complete probabilistic dataset (i.e. all 10000 projections) for Brooms barn (a), Slaidburn (b) and Woburn (c), for the 2050s and three emission scenarios. Results calculated

using 30 sub-samples consisting of 30 projections each. Hurwicz calculated using coefficient of robustness $\alpha=0.5$. Green Z-score calculated using coefficient of robustness $\beta=100$, threshold of acceptability $t=0$, coefficient of optimism $\alpha=0.5$. Outliers included (*).

Comparing the three sites overall, all but Laplace and Green show poor reproducibility from sub-samples of the complete probabilistic dataset, evident from the large range of percentage differences shown (Figure B-4). Laplace and Green exhibit the smallest percentage differences, both in terms of median and range, at all three sites. Maximin exhibit the largest maximum percentage difference at Brooms Barn and Woburn, though at Slaidburn it appears to perform as favourably as Green and Laplace; however, this result can be attributed to the low irrigation demand combined with the worst case rational model underpinning Maximin, which in this example always favoured building no reservoir.

On the basis of these initial results, the Green Z-score produces comparable results to Laplace with sampling. This can be largely attributed to the similar methods used by each approach. Both criteria utilise multiple projections to inform the decision outcome. However, the advantage of the Green Z-score compared to Laplace is that it allows different risk appetites to be accommodated. The parameters underpinning the Green Z-score i.e. coefficient of optimism, coefficient of robustness and threshold of acceptability, can be varied to be representative of decision makers expressing differing degrees of optimism and pessimism. To establish whether variations of Green Z-score could produce more consistent results than current decision criteria from sub-samples, the optimal reservoir capacity is calculated for the Green Z-score using parameters representative of individuals who would typically prefer Laplace, Maximin, Maximax or Hurwicz's criterion, (Table B-3), and for each of the decision criteria, using the complete dataset and each of the 30 samples of 30 projections. It is not possible to compare decision outcomes from the Green Z-score against Minimax regret due to the fundamental differences between these two decision criteria.

Table B-3 Green Z-score parameter setup, showing four decision criteria regularly employed in situations of uncertainty along with four variations of Green Z-score representative of different types of decision maker including the neutral., pessimist, optimist and optimist-pessimist.

Decision maker	Decision criterion	Green Z-score parameters		
		Coefficient of optimism (α)	Coefficient of robustness (β)	Threshold of acceptability (t)
Neutral	Laplace	0.5	100	0
Pessimist	Maximin	0.01	100	0
Optimist	Maximax	1	0.01	0
Optimist-Pessimist	Hurwicz	0.5	0.01	0

The percentage differences in the optimum reservoir capacity between the complete dataset and the sub-samples is then calculated, showing the difference in terms of the decision outcome associated with each of the decision criteria and each variation of the Green Z-score. The results for Brooms Barn are shown in Figure B-5.

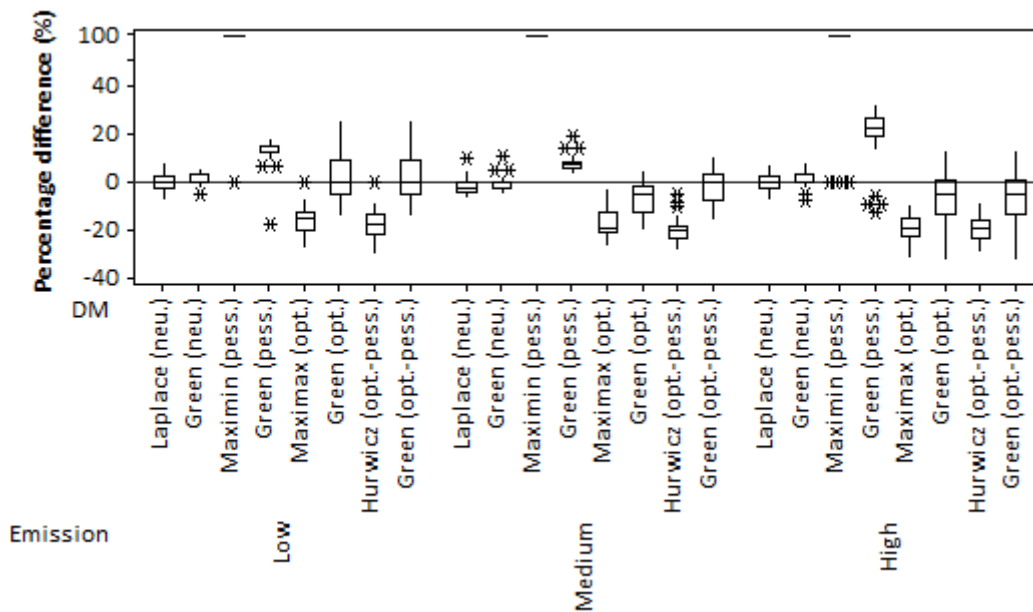


Figure B-5 Percentage difference in optimal reservoir capacity for each of the decision criteria using sub-samples of the probabilistic dataset in place of the complete probabilistic dataset (i.e. all 10000 projections) for Brooms Barn for the 2050s and three emission scenarios. Results calculated using 30 sub-samples consisting of 30 projections each. Hurwicz calculated using coefficient of robustness $\alpha=0.5$. Green Z-score calculated using coefficient of robustness $\beta=100$, threshold of acceptability $t=0$, coefficient of optimism $\alpha=0.5$. Outliers included (*) Four different categories of decision maker (DM) assumed; neutral, pessimist, optimist and optimist-pessimist, each category containing two decision criteria; a current decision criterion and a variation of Green Z-score.

At all three sites and all three emission scenarios, the optimum reservoir capacity from the full dataset is reproduced better under sampling using the Green Z-score than using any of the other decision criteria. At Brooms Barn, while the percentage difference ranges are comparable, each variation of Green Z-score has a smaller median percentage difference compared to current decision criteria. At Slaidburn, the percentage difference between the complete probabilistic dataset and each sub-sample, in terms of the optimal reservoir capacity is zero for every variation of Green Z-score. In contrast, the percentage difference for Hurwicz and Maximax is greater and has a much larger range, suggesting that they would be poorly reproduced from sub-sampling. At

Woburn, Green Z-score largely out performed current decision criteria, while the percentage difference ranges are comparable, the median percentage difference is smaller for Green Z-score compared to current decision criteria.

Discussion

Numerous decision methods and criteria have been developed to assist with decision making under risk and under uncertainty (Ranger et al., 2010). Methods of decision making under risk are not suitable for adaptation planning as the climate change projections on which adaptation is based are not provided with a probability of occurrence (Polasky et al., 2011). In the UK, advances in modelling capabilities and a greater appreciation of uncertainty (Stainforth et al., 2007; Tebaldi and Knutti, 2007) have provided decision makers with a “legitimate and credible” suite of climate change projections in the form of UKCP09 (Tang and Dessai, 2012). However, these advances have come at the expense of saliency. It has previously been suggested that over time climate science may become too complex and thus inhibit decision makers from making sensible decisions, reflected in the perceived saliency gap associated with UKCP09 (McNie, 2007; Sarewitz and Pielke Jr, 2007; Tribbia and Moser, 2008). The diversity of users and lack of specific guidance on how to use UKCP09 may have diminished its usability. Modelling can result in misleading conclusions if projections are not used correctly. As a result, it has been suggested that the value of UKCP09 for real world decision making is limited (Tang and Dessai, 2012).

UKCP09’s saliency gap can be attributed in part to the move from deterministic to probabilistic methods of communicating climate change information. Unfortunately, this move, aimed at quantifying at least part of the underlying uncertainty in the climate change projections and discussed elsewhere (Green and Weatherhead, 2014d) has not yet been accompanied by the development of supporting tools and techniques. A large number of criteria which were previously developed to support decision making have shown to be not appropriate for climate change adaptation because they require more information that can be realistically obtained (Froyn, 2005; Polasky et al., 2011) are crude, overly

complex (Ranger et al., 2010) or not reproducible from sub-samples of the probabilistic dataset (Green and Weatherhead, 2014d).

As a result, a novel decision criterion, the Green Z-score, is developed and applied to a simplified real-world decision problem of designing an on-farm irrigation reservoir. This method is purposely designed to be simple to implement and thereby encourage its use among decision makers that until now were largely reliant on proponents of classical decision theory (French, 1986), some of which are shown here for comparison purposes, to help inform adaptation. Since the Green Z-score is based on MCA it is subject to similar limitations. These limitations are consistent with the general criticisms levelled against MCA and its incorrect application, cost-benefit analysis (CBA) and economic valuation techniques as opposed to an issue with the criterion itself. MCA is subject to a host a potential pitfalls, stemming from incorrectly defining the problem structure, poor performance data, inappropriate capturing of decision-maker preferences, incorrect application of additive utility and duplication or overlapping criteria (Hajkowicz, 2008). The majority of criticisms levelled against MCA are generally associated with the incorrect application of the method as opposed to issues with the method itself.

CBA, which forms the basis of the analysis underpinning the Green Z-score has previously been criticised because it does not generally account for interactions between impacts. Certain individuals may feel more strongly about a project if it imposes both environmental and social costs, regardless of whether these effects are valued independently (Dodgson et al., 2009). Non-monetary elements can also present their own challenges for CBA which may make Green Z-score less suitable, however these elements can sometimes be valued using hedonic pricing (Pearson et al., 2002), travel cost methods (Chen et al., 2004) or other non-market value methods. A further limitation of CBA and by extension the Green Z-score is the time and resources it takes to estimate the financial benefits of an action. However, it can be argued that the time the effort required to estimate financial benefits is proportional to the relative costs of taken said action. “For example, where a tidal barrier is protecting hundreds or thousands of

properties, a proportionate amount of effort in estimating monetised benefits would be justified” (Environment Agency, 2013, p.3). However, while Green Z-score does suffer from some of the limitations of CBA it also borrows a number of positive elements from MCA, specifically its greater flexibility and its ability to resolve trade-offs in a transparent, audible and analytically robust manner. Similarly, Green Z-score can be combined with Monte-Carlo simulation to explore the wider uncertainties and ensure decision outcomes are robust (Dorini et al., 2011). Further work, testing the real-world application of the Green Z-score and whether or not it is preferred to conventional decision criteria with actual decision makers is however recommended.

One of the greatest challenges associated with UKCP09 and its uptake is the sheer number of climate change projections provided. Many impact models are limited by the number of projections they can realistically handle. Some organisations do not have the available resources to utilise these projections, notably in instances where climate change impacts tend to be wide ranging and the potential solutions very diverse. As a result, sample analysis is undertaken to ensure Green Z-score can be reliably reproduced from small sub-samples of the UKCP09 probabilistic dataset and as such is suitable for real-world practice.

Conclusion

Consistent with previous findings, this study found that a number of current decision criteria should not be used with sub-samples of the UKCP09 probabilistic dataset on account that the decision outcomes obtained from them tend to differ substantially to the complete dataset. Certain methods, including Laplace, whose outcomes are successfully reproduced from small samples, are subject to their own criticisms and limitations, both in their assumptions and rational model. Other criteria give different results depending on the sample. Many of the current decision criteria including Laplace and Maximin assume a fixed rational model; such models are rarely accommodating of all decision makers attitudes, particularly when working in the realms of climate change where uncertainty abounds. The apparent lack of flexibility in current decision criteria may account for their limited uptake. While their use has been previously

advocated for adaptation planning, it is much harder to develop a real world case for using them with the current suite of probabilistic climate projections owing to their practical limitations. The Green Z-score, unlike many of the current decision criteria considered here, provides reproducible decision outcomes from sub-samples of the UKCP09 dataset and can accommodate a host of differing risk appetites.

Acknowledgements

The authors would like to thank the Engineering and Physical Sciences Research Council (EPSRC) and HR Wallingford for funding this research and the comments of three anonymous reviewers.

Practical example

A practical example of Green Z-score is provided to guide readers through its calculation. The following decision problem compares three options (option A, B and C) with different outcomes (f_d) across 11 discrete states (s). The minimum ($\min_{d \in D} f_d$) and maximum payoff ($\max_{d \in D} f_d$) of all three options for each state is also shown.

State (s)	Option A	Option B	Option C	$\min_{d \in D} f_d$	$\max_{d \in D} f_d$
1	-10	-15	-3	-15	-3
2	-8	-15	-3	-15	-3
3	-6	-15	-3	-15	-3
4	-4	0	-3	-4	0
5	-2	0	-3	-3	0
6	0	0	-3	-3	0
7	2	0	3.6	0	3.6
8	4	0	3.6	0	4
9	6	15	3.6	3.6	15
10	8	15	3.6	3.6	15
11	10	15	3.6	3.6	15

The following parameters are used:

Coefficient of optimism (α)	Coefficient of robustness (β)	Threshold of acceptability (t)
0.5	80	0

All workings are provided for option A only, all options are summarised at the end of the appendix along with the decision outcome.

The negative performance (B) is initially calculated

$$B = \sum_{s=1}^{s=n} \left(\frac{(f_d - t)}{\left(\min_{d \in D} f_d - t \right)} \right)$$

Where:

fd = option outcome

s = state

t = threshold of acceptability (i.e. 0)

State	fd	t	$(f_d - t)$	$\min_{d \in D} f_d$	$\min_{d \in D} f_d - t$	$\left(\frac{(f_d - t)}{\left(\min_{d \in D} f_d - t \right)} \right)$
1	-10	0	-10	-15	-15	0.67
2	-8	0	-8	-15	-15	0.53
3	-6	0	-6	-15	-15	0.40
4	-4	0	-4	-4	-4	1.00
5	-2	0	-2	-3	-3	0.67
6	0	0	*	-3	*	*
7	2	0	*	0	*	*
8	4	0	*	0	*	*
9	6	0	*	3.6	*	*
10	8	0	*	3.6	*	*
11	10	0	*	3.6	*	*
Total						3.27

* This value is not calculated because $f_d > t$

The overall performance (A) is then calculated

$$A = \sum_{s=1}^n \left(\frac{(f_d - \chi)}{(\max_{d \in D} f_d - \chi)} \right)$$

Where:

fd = option outcome

s = state

$$\chi = \left(\max_{d \in D} f_d - \left(\left(\max_{d \in D} f_d - \min_{d \in D} f_d \right) \cdot \left(\frac{\beta}{100} \right) \right) \right)$$

β = coefficient of robustness

State	fd	$\max_{d \in D} f_d$	$\min_{d \in D} f_d$	χ	$(f_d - \chi)$	$(\max_{d \in D} f_d - \chi)$	$\left(\frac{(f_d - \chi)}{(\max_{d \in D} f_d - \chi)} \right)$
1	-10	-3	-15	-12.60	2.60	9.60	0.27
2	-8	-3	-15	-12.60	4.60	9.60	0.48
3	-6	-3	-15	-12.60	6.60	9.60	0.69
4	-4	0	-4	-3.20	*	*	*
5	-2	0	-3	-2.40	0.40	2.40	0.17
6	0	0	-3	-2.40	2.40	2.40	1.00
7	2	3.6	0	0.72	1.28	2.88	0.44
8	4	4	0	0.80	3.20	3.20	1.00
9	6	15	3.6	5.88	0.12	9.12	0.01
10	8	15	3.6	5.88	2.12	9.12	0.23
11	10	15	3.6	5.88	4.12	9.12	0.45
Total							4.75

*This value is not calculated because $f_d < \chi$

$$z_d = \max_{d \in D} \left((\alpha \cdot A) - ((1 - \alpha) \cdot B) \right) \quad \text{EQ}$$

1.1

Where:

zd = decision outcome

d = option, D = options

α = coefficient of optimism (where $0 < \alpha \leq 1$)

A = overall performance (see EQ1.2)

B = negative performance (see EQ1.3)

Option	A	B	$(\alpha.A)$	$((1 - \alpha).B)$	Green Z-score
A	4.75	3.27	2.37	1.63	0.74
B	6.00	3.00	3.00	1.50	1.50
C	4.94	3.35	2.47	1.68	0.79

The decision outcome (zd) is Option B because it has the highest Green Z-score.

Appendix C A critical comparison of using a probabilistic weather generator versus a change factor approach, irrigation reservoir planning under climate change

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A critical comparison of using a probabilistic weather generator versus a change factor approach; irrigation reservoir planning under climate change

Abstract

In the UK, there is a growing interest in constructing on-farm irrigation reservoirs, however deciding the optimum reservoir capacity is not simple. There are two distinct approaches to generating the future daily weather datasets needed to calculate future irrigation need.

The change factor approach perturbs the observed record using monthly change factors derived from downscaled climate models. This assumes that whilst the climate changes, the day-to-day climate variability itself is stationary. Problems may arise where the instrumental record is insufficient or particularly suspect. Alternatively, probabilistic weather generators can be used to identify options which are considered more robust to climate change uncertainty because they consider non-stationary climate variability.

This paper explores the difference between using the change factor approach and a probabilistic weather generator for informing farm reservoir design at three sites in the UK. Decision outcomes obtained using the current normal practice of 80% probability of non-exceedance rule and simple economic optimisations are also compared.

Decision outcomes obtained using the change factor approach and probabilistic weather generators are significantly different; whether these differences translate to real-world differences is discussed. This study also found that using the 80% probability of non-exceedance rule could potentially result in maladaptation.

Key Words: Irrigation demand, Adaptation, UKCP09, Weather generator, Change factor, WaSim

Background

Water is integral to the UK's ability to grow high quality horticultural produce. In the UK, approximately 150,000 hectares are irrigated during a dry year (Knox et al., 2010). The sustainability of irrigated production is however under threat from competition for water from other sectors, new legislation designed to enhance environmental protection, and climate change (Weatherhead et al., 2008).

Water resources in many catchments are already strained. During summer, many existing water sources become increasingly unreliable and new licenses for summer abstractions are now widely unobtainable or are issued with tight minimum flow or minimum level constraints. Increasingly farmers, agribusiness and water resource managers are being encouraged to build on-farm irrigation reservoirs as part of their water resource strategy to avoid the restrictions and environmental impact of abstraction during summer months (Weatherhead et al., 2008). Climate change is expected to simultaneously increase water demand and reduce water availability (Kang et al., 2009).

The unpredictability of the future climate is perhaps the greatest challenge facing the water industry (Harris et al., 2012). In the UK at least, much of the current infrastructure including irrigation reservoirs were built on the assumption that the climate in which it was built would endure for its entire lifetime – this is no longer the case (Harris et al., 2012).

Two responses have emerged in reaction to the risks posed by future climate change, namely mitigation and adaptation (Füssel, 2007). Mitigation refers to an anthropogenic intervention designed to reduce the sources or enhance the sinks of greenhouse gases. In contrast, adaptation, studied in this paper, refers to “the adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects which moderates harm or exploits beneficial opportunities” (Parry, 2007, p.6). In the UK, adaptation planning emerged as a policy issue in 1997 in response to the formulation of the UK Climate Impacts Programme (UKCIP) (Hedger et al., 2006), receiving renewed interest with the passing of the Climate Change Act 2008 (Tang and Dessai, 2012). The apparent ‘failure’ of high profile climate change protocols (e.g. the Kyoto protocol) has

undermined confidence in the success of mitigation efforts, making adaptation a more attractive surrogate (Harris et al., 2012; Anderson and Bows, 2011; Fung et al., 2011; Sanderson et al., 2011).

A number of approaches to adaptation have been identified. Vulnerability-led adaptation includes methods aimed at identifying and reducing present community/system vulnerability; thereby reducing future exposure to potentially damaging impacts. Scenario-led adaptation, studied here, uses future climate change projections to assess future climate change impacts. Downscaled regional-scale climate scenario data can be fed into impact models; the outputs are then used to inform adaptation, to maximise potential benefits and/or minimise potential risks (Wilby and Dessai, 2010). A hybrid approach, combining elements of vulnerability-led and scenario-led approaches has recently emerged, though is not the focus of this paper (Brown and Wilby, 2012).

Scenario-led adaptation is limited by the financial and technical capacity of the individuals undertaking the adaptation; their risk appetite, the availability of high quality downscaled climate change information and the type of adaptation options being considered (Adger et al., 2005; Dessai et al., 2005). Despite greater awareness of its benefits (Füssel, 2007; Ranger et al., 2010), few real-world cases of scenario-led adaptation decisions have been realised (Tompkins et al., 2010), with large sector and regional differences in the type of adaptation considered. This limited uptake has been attributed to a variety of factors; see Moser and Ekstrom, (2010) for an extensive discussion.

Scenario-led adaptation is used here to model irrigation demand and inform farm reservoir design in a semi-humid climate. A sufficiently long daily weather record is essential to adequately gauge the amount of water required. For the baseline period (1961-1990), irrigation demand calculations are often based on the observed record, though this may be substituted with a synthetic series from a weather generator provided it has been suitably calibrated (Green and Weatherhead, 2014a). Similarly, a sufficiently long record of future daily weather data is required to model irrigation demand under the effects of climate change. Future weather data is typically generated from downscaled global climate

models (GCM). GCM outputs are often only available as monthly values (Holman et al., 2009), which are generally insufficient for modelling dry year supplemental irrigation demand and many hydrological processes. They can however be used to perturb an observed or synthetic daily series using the ‘change factor’ approach (Loáiciga et al., 2000), elsewhere referred to as perturbation or the “delta-change” method (Prudhomme et al., 2002). A change factor is obtained for each month in the future series, these figures are then used to perturb an observed baseline daily series to produce a future series i.e. applying a January monthly change factor of 10% to an observed series would make all of the daily values in the future series for the month of January +10% larger (Holman et al., 2009). A criticism of the change factor approach is that it assumes that the climate variability is stationary, e.g. the same patterns of wet and dry days will occur in the future dataset as in the original baseline (Harris et al., 2012). Despite this, it remains a popular approach, given its relative simplicity and low computation demands (e.g. Daccache et al., 2012). Alternatively, a probabilistic weather generator can be used to generate multiple future time series using perturbed synthetic baselines. Unlike the conventional change factor approach, weather generators are not dependant on the individual having access to a suitably long observed record (Green and Weatherhead, 2014a) nor do they assume that the future climate variability is stationary, making them an attractive tool for supporting robust decision making (Harris et al., 2012; Dessai et al., 2009; Groves and Lempert, 2007; Lempert and Groves, 2010). The change factor approach and UKCP09 weather generator (Wilks and Wilby, 1999; Semenov, 2007) are both examples of statistical downscaling (Wilby et al., 2004), while they are not utilised here, alternative methods collectively referred to as dynamical downscaling techniques also exist (Mearns et al., 2003). An extensive discussion of the merits and weaknesses of these and other downscaling techniques can be found elsewhere and in greater detail (Fowler et al., 2007; Prudhomme et al., 2002).

The primary source of future climate projections in the UK is the UKCP09 dataset (Murphy et al., 2009). UKCP09 provides 10,000 probabilistic climate projections at a 25km scale resolution generated from a perturbed ensemble experiment

using the HadCM3 Global climate model (GCM). These are provided in the format of monthly change factors. Alternatively, daily (and even hourly) projections, and at a finer spatial resolution of 5km², are readily available as outputs from UKCP09's weather generator (Jones et al., 2009). The weather generator provides baseline ("control") and future scenario sequences for three different greenhouse gases emission scenarios (low, medium and high) and for selected 30 year time-slices (centred around the 2020s, 2030s, 2040s, 2050s, 2060s, 2070s and 2080s respectively).

These daily weather datasets can be imported into soil water balance models such as WaSim, freely available via the Cranfield University website, to model the irrigation demand of various crops (Hess and Counsell, 2000). WaSim simulates inflow (infiltration) and outflow (evapotranspiration and drainage) and storage of soil water in response to climate, irrigation and drainage (Depeweg and Fabiola Otero, 2004). WaSim has proven invaluable across a range of previous studies including determining irrigation requirements, optimising water management, assessing the performance of sub-surface drainage systems and studying the effects of climate change on water resources (Depeweg and Fabiola Otero, 2004; Hirekhan et al., 2007; Warren and Holman, 2012). WaSim divides the soil profile into five layers, water moves from upper layers to lower layers when the water content of the respective layer exceeds field capacity. The first three layers are comprised of the surface layer (0-0.15m), the active root zone layer (0.15-root depth) and the unsaturated layer below the root zone (root depth-water table). The remaining 2 layers are comprised of the saturated layer above drain depth (water table – drain depth) and the saturated layer below drain depth (depth drain – impermeable layer). The boundary between the second and third layers changes in response to root growth (e.g. in the case of potatoes, layer 2 has zero thickness when root depth is less than 0.15m, and then increases as the potato develops). Guidance values covering crop development and root depths are provided for selected crops within WaSim, and up to three crops can be combined in a cropping pattern (Hess and Counsell, 2000).

In the field of irrigated agriculture, decision makers have typically relied on the design dry year rule for estimating the volume of irrigation required. A design dry year is defined in the UK as a year with an 80% probability of non-exceedance (roughly equivalent to the older “fourth driest year of five” rule of thumb). This rule of thumb is generally considered the ‘best practice approach’ and forms the basis of most water allocation for UK irrigated agriculture (Weatherhead and Knox, 2000).

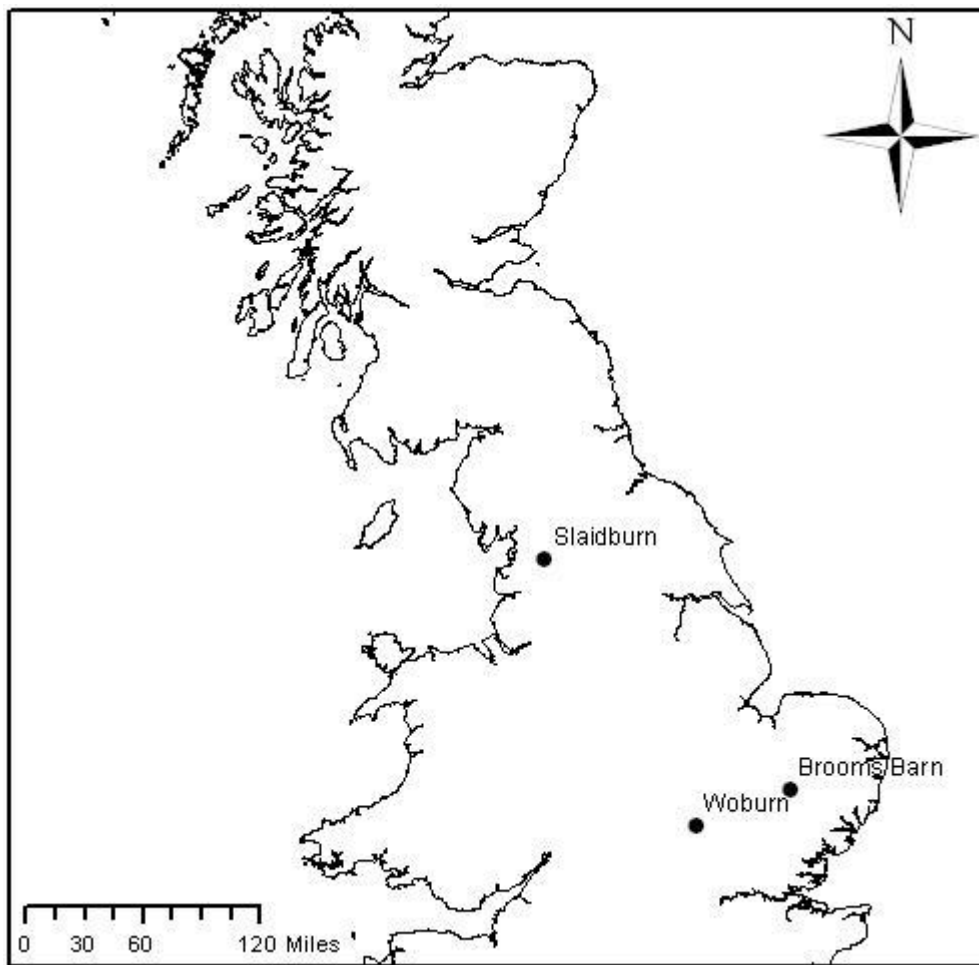
This study explores the difference between using the change factor approach and the UKCP09 weather generator for modelling future irrigation demand and informing reservoir design at three sites in the UK. Decision outcomes are obtained using the 80% probability of non-exceedance rule and an economic optimisation and compared.

Method

A previous study by (Green and Weatherhead, 2014a) found that the weather generator was reasonably calibrated at a number of UK sites. Three sites representing different agro-climatic conditions distributed around the UK were selected as case studies. These particular sites were chosen because they had the most complete record for the baseline period. Brooms Barn is located in the county of Suffolk, near Bury St Edmunds, approximately 30km east of Cambridge and is the driest of the investigated sites. Slaidburn is located in the district of Lancashire, approximately 60km north-west of Leeds and is the wettest site with an average annual rainfall of 1515 mm.year⁻¹ for the baseline period. Lastly, Woburn is situated in the county of Bedfordshire, 50km north-west of London and is marginally wetter than Brooms barn but with slightly lower annual evapotranspiration. Observed climate data was extracted for the baseline period from the weather station at each site. Additional hydroclimatology data for the baseline period is shown in Table C-1.

Table C-1 Weather station sites and records used

Station	Lat.	Long.	Elevation (m AOD)	Average annual (1961-1990)		Data	
				Rain (mm)	ETo (mm)	From	To
Brooms Barn	52.260	0.567	75	588	585	1964	1990
Slaidburn	53.987	-2.433	192	1515	487	1961	1990
Woburn	52.014	-0.595	89	632	564	1961	1990



All 10,000 monthly change factor climate projections were extracted from the UKCP09 sample ensemble for the single 25km² grid square overlying each weather station, for each emission scenario (i.e. low, medium and high) for the 2050s time slice (i.e. 2040-2069). Baseline evapotranspiration and monthly evapotranspiration change factors were estimated using Penman-Monteith (Monteith, 1965); wind speed was assumed to be the same as the observed

baseline (1969-1990) due to the lack of earlier baseline data and future projections of wind speed.

Ten thousand climate projections were simultaneously generated using the UKCP09 weather generator, using the same ID codes to allow direct comparison, again for each weather station and each emissions scenario. The UKCP09 weather generator was previously found to be reasonably calibrated at these sites with the exception of some extreme events (which are beyond the scope of our analysis and do not impact the reservoir design) (Green and Weatherhead, 2014a).

As the weather generator offers a much greater spatial resolution of 5km², data was generated for a grouping of 25 individual grid squares (i.e. a combined area of 25km²) overlying each weather station, to be directly comparable with the 10,000 member ensemble 25km² grid square. It should be noted that the weather generator and 10,000 member sample ensemble spatial grids differ slightly in their orientation which may create subtle differences in the projected climate, though because of the large areas used, the impact is considered somewhat negligible. Despite this, the potential impacts on the outcomes of this study are an acknowledged limitation.

Next, WaSim was used to model irrigation demand at each site. In its basic format WaSim is not capable of processing multiple climate files succinctly, so a modified version was developed and employed for this study to read-in multiple climate files and output a single results file containing the daily irrigation demand for each of the 10000 climate files. A potato crop was simulated with a planting depth of 0.15m, max root depth of 0.7m and planting date of 1st April. A rule based irrigation schedule was modelled based on best practice guidelines including scab control (Defra, 2005). This schedule consisted of 4 periods (1 non-irrigation followed by 2 irrigation and 1-non irrigation), applying 15mm of water early in the growing season whenever the root zone deficit exceeded 18mm during period 2 (15th May-30th June) and applying 25mm of water whenever the root zone deficit exceeded 30mm during period 3 (30th June-31st Aug). Irrigation early in the growing season is essential for some varieties for minimising the chance of potato

scab, a common bacterial blight which can severely reduce the market value of produce (Liu et al., 1996). Irrigation is also important for promoting higher tuber numbers, accelerating crop canopy growth, reducing the chance of uneven growth and thumbnail cracking and reducing crop damage during harvesting (Defra, 2005). The soil type was set as sandy loam, which is the dominant soil type for potato crops in England, with an assumed saturation of 43.3% and field capacity of 24.5%.

The irrigation demand was calculated for each year in the 10,000 x 30 year sequences for each site and emission scenario, using both the change factor and weather generator datasets. The values within each sequence were then ranked from smallest to largest. The irrigation demand during the design dry year, (referred to hereafter as 80% dry year irrigation demand) was calculated for each of the 10,000 sequences, using the 80% probability of non-exceedance rule. The median, mean, quartile and extreme values for each site, emission scenario and dataset were identified.

For the economic evaluation, typical costs and benefits for clay agricultural reservoirs were obtained from a concurrent study (Weatherhead et al., 2008). The economic benefit of the water contained within each reservoir was calculated on the basis of average water use, assuming an average net benefit (for potatoes) of £1.56/m³ of water used (Morris et al., 1997). Earthwork costs were assumed to be £1.125 per m³ of earth moved, plus an additional 15% reflecting site investigation costs. A further £20k was added, representing the assumed connection costs of 3-phase electricity. Annual OPEX was assumed to be 1% of CAPEX, representing the low maintenance cost of clay reservoirs (Weatherhead et al., 2008). Each of the 10,000 sequences was then used to calculate the net present value (NPV) of a range of reservoir sizes, with usable storage capacities equivalent to 0 to 1000mm.year⁻¹ for the area irrigated. NPV provides a measure of the present value of the difference between the assumed costs and benefits of a decision. NPV was calculated by discounting the annual net benefit of the reservoir less OPEX costs with a lumped (non-discounted) CAPEX in year 0, assuming current government discount rate guidelines of 3.5% on investments of

up to 30 years (Treasury, 2003). Each reservoir was assumed to last 30 years, representing their typical life cycle. The optimum reservoir capacity, defined as the size providing the highest NPV was calculated for each of the 10,000 sequences. The median, mean, quartile and extreme values for each site, emission scenario and dataset were identified as before.

The Mann-Whitney U-test (Mann and Whitney, 1947) was used to establish whether there was significant differences between the change factor and weather generator datasets in terms of both the 80% dry year irrigation demands and the optimum reservoir capacities. The Mann-Whitney U test was chosen due to the non-parametric nature of the data even after applying transformations. The Mann-Whitney U test is used to test the equality of two population medians. It is considered the non-parametric alternative to the 2-sample t-test, it assumes that the populations are independent and have a similar distribution shape. Unlike the 2-sample t-test it does not require the two populations to be normally distributed.

In addition, a sensitivity analysis was undertaken to establish how sensitive the decision outcome was to the choice of discount rate, benefit of the water and earthwork costs. Each parameter was varied in turn, keeping the other parameters fixed, and the median optimum reservoir capacity identified, calculating the percentage difference before and after varying each parameter. The discount rate was initially fixed at 3.5%, water benefit at £1.56/m³ and earthworks at £1.1.25/m³, and subsequently scaled up and down using a linear coefficient.

Results and Discussion

The 80% dry year irrigation demands were compared between the change factor and weather generator sequences for each sites and emission scenario Figure C-1. The median 80% dry year irrigation demand was similar across both datasets. Both also had a similar interquartile and extreme range. These results support the assumption that the weather generator was reasonably calibrated with the observed record (Green and Weatherhead, 2014a) and suggest that using the UKCP09 weather generator instead of the conventional change factor approach may not necessarily lead to more robust decision making.

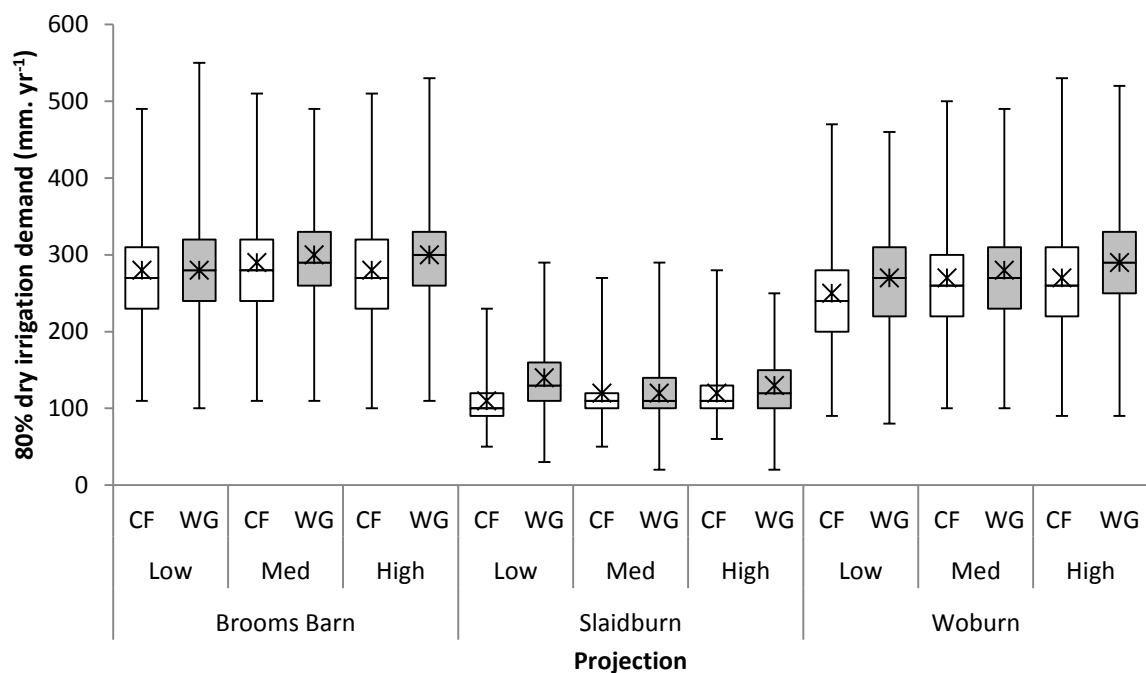


Figure C-1 Median (-), mean (X), quartile and extreme values of the 80% dry year irrigation demand for the change factor (CF) and weather generator (WG) sequences for each site and emission scenario.

Next, the economic performance of various reservoir capacities generated using the full 10000 change factor and weather generator sequences were compared against each other for each site and emission scenario. Figure C-2 shows the results obtained for the site of Woburn using the medium emission scenario. Despite subtle differences in the projected NPV, both datasets showed a similar trend in NPV against reservoir capacity. The weather generator projected a higher NPV for most reservoir capacities, based on the median projection, with the exception of small reservoirs with a capacity of less than 100mm.yr⁻¹. The NPV range (i.e. the difference between the max payoff and minimum payoff for each reservoir size) is initially quite narrow and increases with reservoir capacity. The NPV range is larger for the weather generator dataset than for the change factor dataset for all the reservoir capacities considered. For the change factor dataset, the median optimum reservoir capacity was 340mm.year⁻¹. In contrast, the weather generator estimated the median optimum reservoir capacity to be

marginally smaller at 320mm.year⁻¹ but with a 20% larger NPV. Similar results were recorded for all three emission scenarios for all three sites.

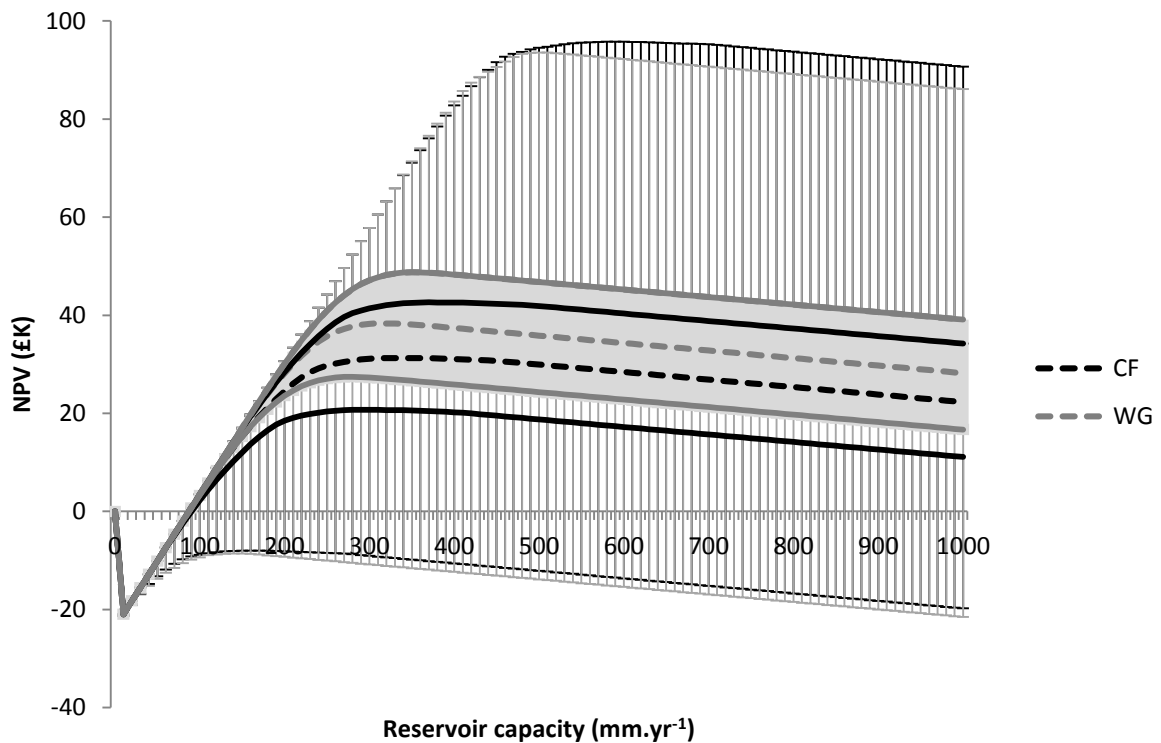


Figure C-2 Median, quartile and extreme values of NPV against reservoir capacity for the change factor (CF) and UKCP09 weather generator (WG) sequences for the Woburn site and medium emission scenario.

Statistical analysis was undertaken to establish whether there was significant difference between using the weather generator and change factor datasets in terms of 1) the 80% dry year irrigation demand and 2) the optimum reservoir capacity. The 80% dry year irrigation demand values obtained using the weather generator dataset were significantly greater than those from using the change factor dataset. In contrast, the optimum reservoir capacities from the weather generator dataset were significantly lower than from the change factor dataset. However, while the differences were statistically significant at the 95CI (Table C-2), the difference in the 80% dry year irrigation demand was generally less than 25mm.year⁻¹, which is only the depth of a typical single application of water. The difference in the optimum reservoir capacities was similarly small (though generally >25mm.year⁻¹), with the exception of the Brooms Barn site. These

results again suggest that using the weather generator in place of the conventional change factor, while theoretically leading to more robust decision making, in reality is unlikely to greatly affect the decision outcome.

Table C-2 Results of Mann-Whitney U-test statistical analysis comparing 80% dry year irrigation demand and optimum reservoir capacity obtained using economic optimisation with change factor (CF) and weather generator (WG) datasets, showing median reservoir capacity, whether they are significantly different and using 95 confidence interval (95CI).

Site	Brooms Barn											
Criteria	80% Dry year irrigation demand						Optimum reservoir capacity					
Emission scen.	Low		Med		High		Low		Med		High	
Data source	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG
Res. capacity	270	280	280	290	270	300	360	310	370	320	370	330
Sig. difference?	Yes		Yes		Yes		Yes		Yes		Yes	
P-value (95CI)	0.00		0.00		000		0.00		0.00		0.00	
Site	Slaidburn											
Criteria	80% Dry year irrigation demand						Optimum reservoir capacity					
Emission scen.	L		M		H		L		M		H	
Data	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG
Res. capacity	100	130	110	110	110	120	0	0	0	0	0	0
Sig. difference?	Yes		Yes		Yes		Yes		Yes		Yes	
P-value (95CI)	0.00		0.00		0.00		0.00		0.00		0.00	
Site	Woburn											
Criteria	80% Dry year irrigation demand						Optimum reservoir capacity					
Emission scen.	Low		Med		High		Low		Med		High	
Data source	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG
Res. capacity	240	270	260	270	260	290	320	300	340	320	340	320
Sig. difference?	Yes		Yes		Yes		Yes		Yes		Yes	
P-value (95CI)	0.00		0.00		0.00		0.00		0.00		0.00	

Finally, the optimum reservoir capacity was directly compared with the dry year irrigation demand calculated using a range on probability of non-exceedance values (80%, 85%, 90%, 95% and 100%). Based on these initial findings, the

80% probability of exceedance rule appears to underestimate the optimum reservoir capacity at Brooms Barn and Woburn and overestimate the optimum reservoir capacity at Slaidburn (the wettest site), with a difference of between -120 to +100mm.ha⁻¹ (Figure C-3). The 95% probability of non-exceedance rule had a smaller difference of between 0 to +170mm.year⁻¹. Visual comparison would suggest that the 95% probability of non-exceedance rule is much closer to the optimum reservoir capacity at the sites of Brooms Barn and Woburn. However at the site of Slaidburn, all five probability of non-exceedance rules tested appear to considerably overestimate the optimum reservoir capacity (see Figure C-3). This result should serve as a warning to those stakeholders who do not consider the underlying economics of their decision; blind use of probability of non-exceedance rules can lead to maladaptation with stakeholders either over-designing or under-designing their assets.

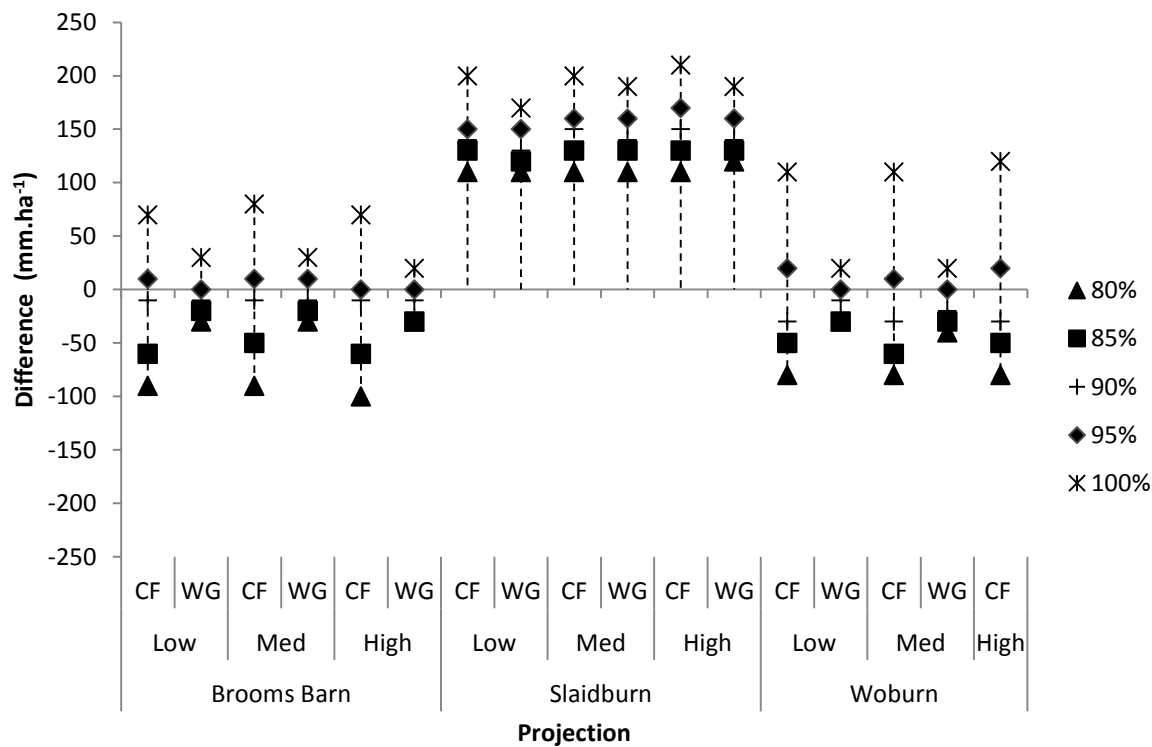


Figure C-3 Differences between the median dry year irrigation demands using 80% to 95% exceedance rules and the median optimum reservoir capacity, for the change factor (CF) and weather generator (WG) sequences for each site and emission scenario.

The results of this study are dependent on several assumptions including 1) discount rate, 2) earth work costs and 3) monetary benefit of the water. Each of these variables is a potential source of uncertainty and may potentially affect the optimum reservoir capacity. As a result, a sensitivity analysis was undertaken to establish whether altering these parameters changed the perceived optimum reservoir capacity.

The sensitivity analysis is presented here for the site of Woburn, for the medium emission scenario and the weather generator dataset. Similar results were obtained for the other sites and emission scenarios and for the change factor dataset. The optimum reservoir capacity was largely insensitive to the discount rate, evident from the near horizontal line, with larger discount rates slightly favouring smaller reservoirs (Figure C-4). The reservoir capacity was more sensitive to earthworks costs, with larger earthworks costs favouring smaller reservoirs, again as expected. The value of the water in the reservoir had the largest effect on the optimum reservoir capacity; below £0.78.m⁻³ the reservoir produced a negative NPV and was no longer economically viable at this site. Increasing the value of water above £1.56.m⁻³ had surprisingly little effect on the optimum reservoir capacity, increasing it by only 9.7% even up to a value of £4.68.m⁻³; this reflects the point that useful capacity is limited by demand, with decreasing returns to additional capacity.

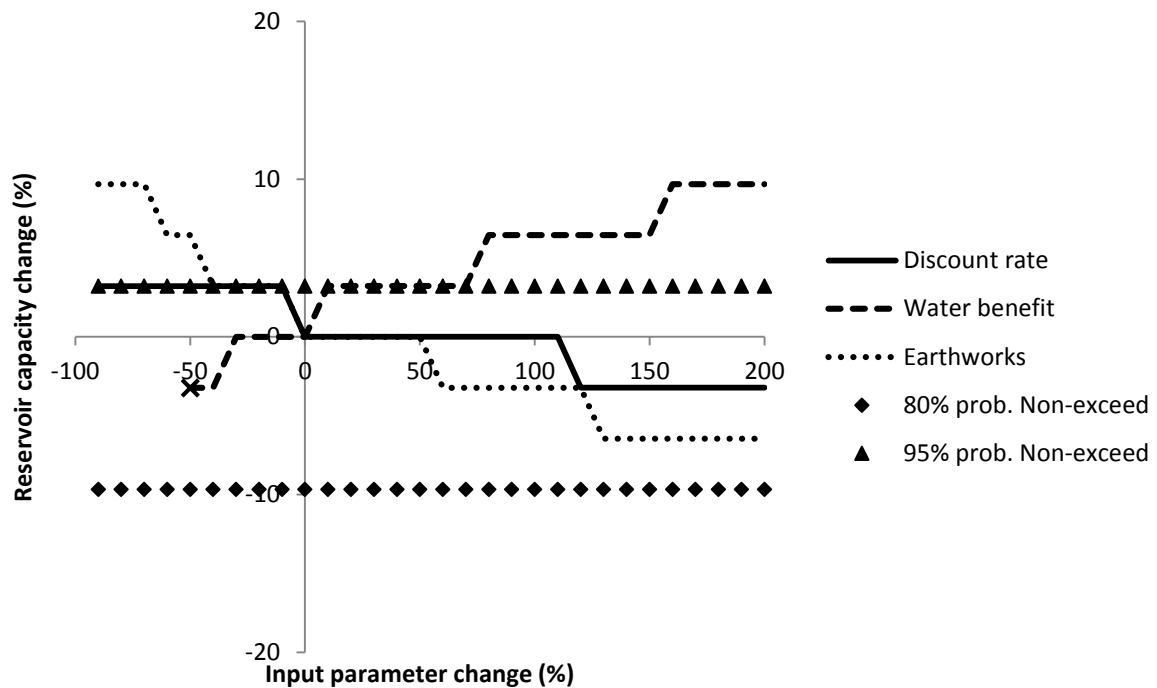


Figure C-4 Sensitivity analysis comparing optimum reservoir capacity against discount rate, water benefit and earthworks cost, showing changes relative to base parameter values, for the Woburn site and medium emission scenario. The 80% and 95% dry year irrigation demands are also shown for comparison.

These variations in median optimum reservoir capacity were subsequently compared to the capacities given by the simpler % exceedance rules, in this case the 80% and 95% dry year irrigation demand. For the Woburn site and the base variable values, the 95% probability of non-exceedance rule out performs the 80% probability of non-exceedance rule (Figure C-4). At larger discount rates (>7%) the 80% rule works better, and for lower earthwork costs (less than £1.80.m-3) the two rules are equally close. For all water values, the 95% probability of non-exceedance rule was nearer the optimum value, but both rules failed to show that the reservoir was no longer economically viable when the water value was less than £0.78.m-3. More case studies would be needed to confirm theses are general results, but they suggest that the 80% rule may be misleading.

It should be noted that these findings are conditional on the view that the median optimum reservoir capacity of the 10,000 sequences represents the most

appropriate course of action (akin to the ‘Laplacian’ view of investment appraisal) (French, 1986). Decision makers who are particularly risk averse or risk seeking may disagree with this assumption and may instead use the quartile or even best/worst case projections, though for the vast majority of stakeholders our stated assumptions should suffice.

Global climate models (GCM) providing “high” resolution daily projections are few in number and those which do are considered less accurate (Huth et al., 2001). As a result, GCM climate change projections often need to be downscaled both spatially and temporally before they can be of any use for decision makers. Numerous downscaling approaches are available, including but not limited to the change factor approach and UKCP09 weather generator considered here. Different downscaling techniques come with their own advantages and disadvantages; see Wilby et al., (2004) and Fowler et al., (2007) for extensive reviews. The UKCP09 weather generator is theoretically better than the conventional change factor approach, given that it allows for non-stationary variability to be simulated and thus incorporated into climate change risk assessments and adaptation planning (Harris et al., 2012). The UKCP09 weather is however not without its flaws, a previous study by Tham et al., (2011) found that the weather generator initially released with UKCP09 was unable to reproduce observations of key climate variables including sunshine duration and solar irradiation.

In later versions of the UKCP09 weather generator, modifications were made to the weather generator to improve its predictive capabilities, which were later verified by Eames et al., (2012). They found that the weather generator was capable of producing weather data that was consistent with historical monthly observations of wind, speed, direct irradiation, diffuse irradiation, global irradiation, maximum temperature, minimum temperature and mean temperature. This result is consistent with previous findings by Green and Weatherhead, (2014a) which showed that the UKCP09 was capable of reproducing observed precipitation and evapotranspiration and annual irrigation demand reasonably well. Eames et al., (2012) also noted that subsequent iterations of the UKCP09

weather generator had issues reproducing a realistic distribution of sunshine hours and direct and diffuse irradiation which can lead to absurd conclusions. We expect that the UKCP09 weather generator will be gradually improved over time to reduce or remove these concerns; while they did not affect the findings of this study they may have implications for other applications where hourly data is of high importance.

A criticism of the change factor method, as previously noted, is that it assumes that the temporal and spatial structure of future precipitation and evapotranspiration remains unchanged (Harris et al., 2012; Diaz-Nieto and Wilby, 2005; Minville et al., 2008; Fowler et al., 2005). In some situations, it is necessary to evaluate changes in climate variability and not just changes in means (Semenov et al., 1998). Despite this, the change factor approach remains popular because of its simplicity and is useful for converting monthly change factors into daily projections needed to model most hydrological processes without incurring excessive expense (Minville et al., 2008).

Conclusions

This study found that use of a weather generator not greatly alter the decision outcome compared to using the conventional and relative crude change factor approach, suggesting that the changes in day-to-day climate variability that is simulated by the weather generator are not significant enough to warrant action when informing irrigation reservoir design. This result is contrary to the expectation that the UKCP09 weather generator lends itself to more robust decision making; in reality the difference between the two approaches is negligible.

The core benefits of the weather generator may continue to make it an attractive tool to use, those being that it provides hourly climate data and readily available evapotranspiration data. Whether these benefits outweigh its fundamental limitations including the poor simulation of extreme meteorological events, is subject to the sensitivity of each application and the user's requirements. The study also found that the "best-practice" approach of using the 80% probability of

non-exceedance rule is inadequate and designers should instead investigate the fundamental economics (e.g. NPV) that underpin the decision making process.

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Appendix D Irrigation demand modelling using the UKCP09 weather generator: Lessons learned

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Abstract

The determination of irrigation demand is typically based on crop modelling using a long historic record of local daily weather data. However, there are rarely adequate weather station records near to given sites; often any local records cover a limited number of years, are incomplete, costly or are of poor quality.

This paper examines whether version 1 of the UKCP09 weather generator can provide a simpler and effective method of calculating irrigation demand with sufficient accuracy for regulatory and design purposes.

The irrigation demands at seven sites distributed around England were modelled using the UKCP09 baseline climatology and compared to results modelled using daily observed weather records. For the design dry year used for irrigation planning, the weather generator replicated the observed conditions with reasonable accuracy. The weather generator was however less successful at replicating extreme dry years.

These results are encouraging but also provide a note of caution for the use of these generated datasets for studying current irrigation demand and by implication for modelling future needs under climate change. The study also demonstrated a simple sub-sampling approach for reducing the processing demands if using the dataset in more complex models, though this would not remove any underlying error.

Keywords: irrigation demand, UK, UKCP09, WaSim, weather generator

Introduction

Water is essential for sustainable development, economic growth and poverty reduction, across a variety of sectors including agriculture, energy, environment and health (Stakhiv and Stewart, 2010). A reliable supply is integral to many industries including the irrigated agri-business, and water stress has obvious implications for food production, rural businesses and rural employment (Knox et al., 2009; Daccache et al., 2011).

While the volume abstracted for irrigation in the United Kingdom is relatively small, it peaks during the summer months when water resources are most strained, and can create conflict with other demands for water, most notably for the public water supply and environmental protection (Daccache et al., 2011). Summer water resources in many catchments are already fully licensed, and some are over licensed or even over abstracted (Knox et al., 2010). There is pressure to reduce excessively large licences. Where water is available, applicants for renewal of existing time-limited licences and/or additional abstractions are required to prove a “reasonable need” for the water they request.

Potatoes (*Solanum tuberosum* L.) are the most important irrigated crop in the UK, accounting for 43% of the total irrigated area and 56% of the total volume of water abstracted in the UK (Knox et al., 2009). Their sparse root system (85% of the root length is concentrated in the upper 0.3 m soil layer) means they are particularly sensitive to moisture stress (Opena and Porter, 1999). The UK potato industry has changed dramatically in recent decades, from a relatively small sector consisting of individual farms to a much larger consortium of major agri-businesses. This shift in production has been principally attributed to rising demand for high quality produce, most easily met by irrigation; this has in turn led to greater interest in irrigation demand modelling across the industry as a whole (Knox et al., 2010).

Irrigation demand in a highly variable climate such as the United Kingdom's is best predicted by crop modelling using a long historic daily weather record (generally at least 20 years), precipitation and evapotranspiration being the primary variables of interest (Kilsby et al., 2007). Unfortunately, there are rarely

adequate weather records near to a given site; local weather stations often cover only a limited number of years, have incomplete or corrupted records, and/or do not record all the variables required to accurately calculate evapotranspiration. There are also significant costs associated with obtaining and validating the data. As a result, the analysis is often based on a synthesis of limited local records with more complete or longer term data from elsewhere, or an interpolation between data from distant stations.

Weatherhead and Knox, (2000) developed a procedure for calculating design dry-year irrigation demands (defined as meeting the demand in 80% of years) for use by the regulator in England, the Environment Agency (Mathieson et al., 2002). They mapped the country into seven agro-climatic zones based on Potential Soil Moisture Deficit and produced look-up tables for each zone, three soil classes (based on soil water availability) and the major irrigated crop categories. However this procedure reveals little about demand in other years, or how varying farm practices or crop varieties could influence demand.

The United Kingdom Climate Projections 2009 (Murphy et al., 2009), or “UKCP09”, dataset provides baseline and future probabilistic climate projections at a 25 km scale resolution generated from a perturbed ensemble experiment using the HadSM3 Global climate model (GCM) and other climate models, but these are only available as monthly values, which is insufficient for modelling supplemental irrigation demand. In contrast, baseline and future daily (and even hourly) projections, and at a finer spatial resolution of 5 km, are available from UKCP09’s integrated weather generator (Murphy et al., 2009). Weather generators, such as the UKCP09 weather generator, have been increasingly used to downscale GCM outputs. They are particularly advantageous as they allow climate variability and uncertainty to be modelled. Historically, they were typically used to supplement observed records, in situations where data is missing or potentially erroneous (Wilks and Wilby, 1999). By comparing the weather generator’s synthetic series against the observed record we can effectively quantify the skill of a weather generator (Min et al., 2011). Once calibrated, weather generators require no manual data input or prior knowledge

of climate modelling, allowing for non-specialist end users to better gauge the extent and magnitude of potential impacts associated with climate change. Their growing popularity has in turn led to more widespread uptake across the industry as a whole.

The UKCP09 weather generator is based around a stochastic rainfall model; other climate variables are then derived from the rainfall state using statistical relationships. Five rainfall states are considered; dry today/dry yesterday, dry today/wet yesterday, wet today/wet yesterday, wet today/dry yesterday and dry today/dry yesterday and dry the day before (Eames et al., 2012). It provides statistically credible synthetic climatology that is consistent with the underlying baseline and probabilistic future climate projections (Jones et al., 2009). However, it is not intuitively clear that the result will be adequate for modelling irrigation water use, which depends mainly on the frequency and extremeness of dry periods of 10 days or more in a humid climate such as England.

The high spatial and temporal resolution of the UKCP09 weather generator make it an attractive candidate for use with daily soil water balance models such as WaSim (Hess and Counsell, 2000) and DSSAT (Daccache et al., 2011) which are already being used for irrigation demand estimation. Originally designed as a learning and education aid, WaSim has proven itself invaluable across a range of hydrological studies including determining irrigation requirements, optimising water management and assessing the performance of sub-surface drainage systems (Depeweg and Fabiola Otero, 2004; Hirekhan et al., 2007). WaSim was selected for this (and other) studies largely on the basis of its flexibility, data availability and demonstrated value as a research tool (Holman et al., 2009; Fasinmirin et al., 2012).

The UKCP09 weather generator does suffer from certain known limitations (discussion later). While it can be updated and improved (and many of these limitations reduced), it is important to encourage its use for real world decision making (Harris et al., 2012). However, for this to occur it must be first demonstrated that the UKCP09 weather generator can provide synthetic climate series which are consistent with the observed records and that a decision maker

would arrive at the same (or similar) decision had they used the weather generator instead of the observed record. Without this evidence, its continued use for irrigation demand modelling will also be brought into question, with obvious implications for future planning.

This aim of this paper is to establish whether the UKCP09 weather generator can provide an effective tool for irrigation demand modelling which is consistent with the observed record. Two sources of recorded data were considered, from the Met Office's interpolated 5 km grid and directly from weather stations. Generated climate variables at seven sites are first compared with the equivalent observed records. The average annual irrigation demand, the 80% dry year demand (following the current best practice approach for irrigation design) and the extreme year demand for a potato crop are then calculated for each dataset. These are compared to establish whether a decision maker would arrive at the same decision if they used the weather generator instead of the observed record.

Method

Baseline climatology (1961-1990) is available through the UK Met Office in the form of an interpolated 5 km grid covering the entire UK, derived from the observed record. Thirty-six individual climate parameters are available, including temperature, precipitation, sunshine hours, relative humidity and wind speed. The interpolated grid was generated using inverse-distance weighted interpolation, by means of an irregular spaced and evolving network of observed weather stations (UK Met Office, 2014a). However, this database is limited to average monthly values (UK Met Office, 2014b). Daily records can be obtained at actual weather station sites from the BADC (British Atmospheric Data Centre, 2014).

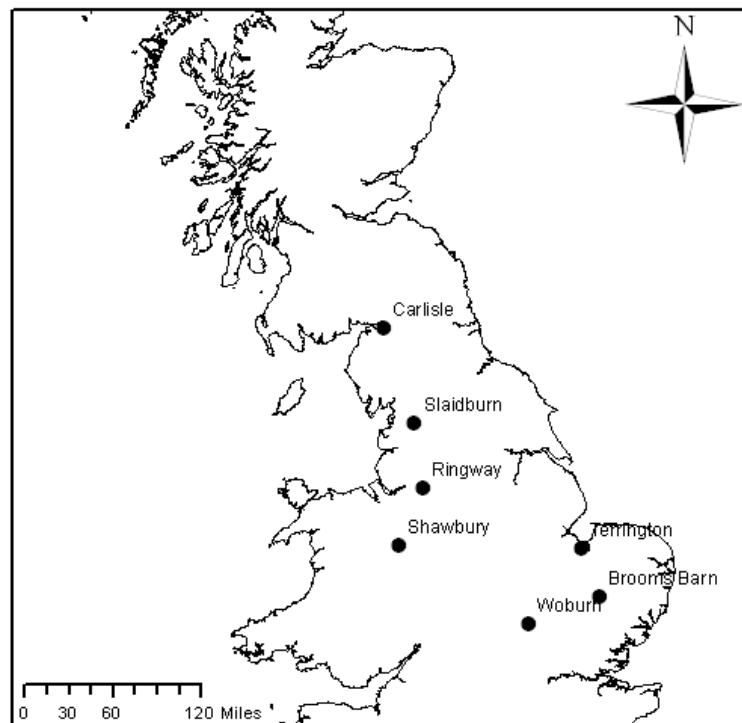
Climate baselines

Seven sites (Table D-1) were selected to represent a range of agro-climatic conditions, the spatial distribution of irrigated potatoes and on the basis of the quality and completeness of their daily records during the baseline period. For most sites that covered most of the 30 year 1961-1990 baseline period. Baseline observed daily data, and monthly averages at a 5 km grid resolution, were

obtained, and duplicate and spurious data entries were removed prior to data processing. Evapotranspiration was derived using Penman-Monteith ((Monteith, 1965)), using the period 1969-1990 due to the lack of earlier wind speed data for the interpolated grid

Table D-1 Weather station sites and records used

Station name	Station ID	Elevation (m AOD)	Latitude	Longitude	Data from	Data to
Brooms Barn	435	75	52.260	0.567	1/1/1964	31/12/1990
Carlisle	1070	26	54.934	-2.962	1/1/1961	31/12/1988
Ringway	1135	69	53.356	-2.279	1/1/1963	31/12/1990
Shawbury	643	72	52.794	-2.663	1/1/1962	31/12/1990
Slaidburn	507	192	53.987	-2.433	1/1/1961	31/12/1990
Terrington	406	2	52.745	0.290	1/1/1963	31/12/1990
Woburn	458	89	52.014	-0.595	1/1/1961	31/12/1990



UKCP09 weather generator

The UKCP09 weather generator provides statistically equivalent 30 year daily weather sequences for any given time slice and emission scenario of interest. The UK Climate Impacts Programme (UKCIP) suggests a minimum of 100 sequences should be used in analyses and modelling. For this study, therefore, 300 control (baseline) sequences were generated for each of the 5 km pixels where the seven sites are located using version 1 of the UKCP09 weather generator. This corresponds to 100 sequences for each of the three climate change scenarios (although the baseline sequences without climate change are of course equivalent). Whether fewer sequences would give similar results is discussed later.

As an initial check, the weather generator baselines were compared to the observed record at each weather station in terms of a) monthly precipitation and b) monthly evapotranspiration, given the importance of these variables for modelling irrigation demand.

The weather generator baselines values were then compared to the Met Office's interpolated grid values. Statistical analysis, using a Mann Whitney U-test, was undertaken in order to establish whether there was a significant difference in these basic parameters between the weather generator outputs, the observed records and the interpolated grid.

Irrigation demand

Next, WaSim was used to model irrigation demand at each site. WaSim undertakes a multi-layer one-dimensional, daily, soil water balance; it simulates inflow (infiltration) and outflow (evapotranspiration and drainage) and storage of soil water in response to climate, irrigation and drainage (Depeweg and Fabiola Otero, 2004). WaSim divides the soil profile into five layers, water moves from upper layers to lower layers when the water content of the respective layer exceeds field capacity. The first three layers are comprised of the surface layer (0-0.15 m), the active root zone layer (0.15-root depth) and the unsaturated layer below the root zone (root depth-water table). The remaining two layers are comprised of the saturated layer above drain depth (water table – drain depth) and the saturated layer below drain depth (depth drain – impermeable layer). The

boundary between the second and third layers will change in response to root growth (e.g. in the case of potatoes, layer 2 will have zero thickness when root depth is less than 0.15 m, and will then increase as the potato develops).

WaSim requires rainfall and evapotranspiration data in order to run. An additional utility, WaSimET, is available for calculating evapotranspiration from climate data using Penman-Monteith, Food and Agriculture Organisation (FAO) Modified-Penman or Penman methods. Guidance values covering crop development and root depths are provided for selected crops within WaSim, and up to three crops to be combined in a cropping pattern (Hess and Counsell, 2000). Root development is assumed to increase from the planting depth to the maximum depth following a sinusoidal curve between the planting date and the maximum root date. Irrigation schedules can be set up as either calendar or rule based. Calendar schedules assume a fixed irrigation date (e.g. 30 days after planting – irrigate 60 mm), whereas rule based scheduling, used in this study to simulate actual farmer behaviour in England, divides the cropping season into a series of irrigation and non-irrigation periods on the basis of rules governing the frequency and volume of irrigate application. In its basic format WaSim is not capable of processing multiple climate files succinctly, so a modified version was developed and employed for this study to speed up data processing.

A potato crop was simulated with a planting depth of 0.15 m, max root depth of 0.7 m and planting date of 1st April. An irrigation schedule was chosen based on best practice guidelines including scab control (Defra, 2005). This schedule consisted of 4 periods (1 non-irrigation followed by 2 irrigation and 1-non irrigation), applying 15 mm of irrigate early in the growing season when the root zone deficit exceeded 18 mm during period 2 (15th May-30th June) and applying 25 mm irrigate when the root zone deficit exceeded 30 mm during period 3 (30th June-31st Aug). Irrigation early in the growing season is essential for some varieties for minimising the chance of potato scab, a common bacterial blight which can severely reduce the market value of produce (Liu et al., 1996). Irrigation is also important for promoting higher tuber numbers, accelerating crop canopy growth, reducing the chance of uneven growth and thumbnail cracking

and reducing crop damage during harvesting (Defra, 2005). The soil type was set as sandy loam, which is the dominant soil type for potato crops in England, with an assumed saturation of 43.3% and field capacity of 24.5%. In reality soil types will differ between the investigated sites, though for the purpose of this study they were assumed to be the same for consistency.

At each site, the annual irrigation demand was calculated each year in the 300 x 30 year generated sequences and for the observed weather record. Statistical analysis, using a Mann Whitney U-test, was then undertaken to establish whether there was a significant difference between the average annual irrigation demand and inter-annual standard deviation from the weather generator sequences and the observed record. Transformations were subsequently applied where the data was not normally distributed. If it was still not normally distributed, a non-parametric test (Mann Whitney U-test) was used. Where the data was normally distributed, either before or after transformation, a 2 sample T-test was used.

Each sequence was then ranked from smallest to largest based on the annual irrigation demand; for the 300 generated sequences this gave 300 values for the “driest” year, the second driest etc. The 80th percentile design dry year values were then identified, and again compared to the observed values. The extreme dry year values were similarly compared.

Finally, a short study was undertaken to establish whether it would be possible to use fewer weather generator sequences and still obtain reasonable accuracy. The following equation, (e.g. Lohr 1999) was applied.

$$N_0 = z^2(s^2/e^2)$$

Where: N = minimum sample size

z (for 95% Confidence Interval) = 1.96

s= standard deviation

e= error coefficient

Results

Climate baselines

The results revealed that the observed and weather generator datasets of monthly average precipitation and evapotranspiration were significantly different at the majority of the sites (Table D-2). The observed record also exhibited a much larger precipitation standard deviation than the weather generator at all the sites (e.g. Figure D-1). Observed and weather generator average monthly precipitation was significantly different at the 95% confidence interval at the majority of the sites. The weather generator and interpolated grid values also provided significantly different results at the majority of sites. These findings were unexpected given that the weather generator was itself calibrated on observed daily rainfall totals and other weather variables.

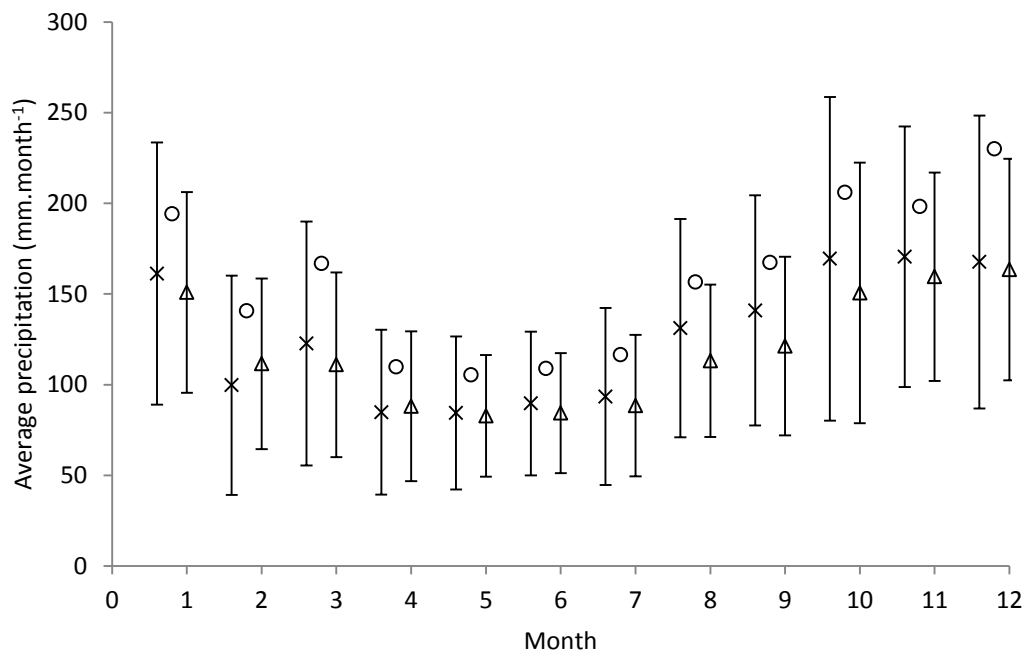


Figure D-1 Monthly precipitation at the Slaidburn site for the baseline period 1961-1990, comparing observed weather station records (X), weather generator datasets (Δ) and interpolated grid values (o). Error bars represent one standard deviation above and below the observed and average weather generator record.

Table D-2 Test for significant differences comparing observed and weather generator monthly precipitation and monthly evapotranspiration and interpolated grid and weather generator monthly precipitation and monthly evapotranspiration at the 95% confidence interval for all seven sites.

Site	Precipitation p-value	
	Observed versus weather generator	Interpolated grid versus weather generator
Brooms barn	0.002	0.000
Carlisle	0.068	0.315
Ringway	0.000	0.000
Shawbury	0.002	0.432
Slaidburn	0.495	0.000
Terrington	0.092	0.269
Woburn	0.000	0.000

Site	Evapotranspiration p-value	
	Observed versus weather generator	Interpolated grid versus weather generator
Brooms barn	0.004	0.131
Carlisle	0.033	0.005
Ringway	0.000	0.000
Shawbury	0.002	0.027
Slaidburn	0.071	0.000
Terrington	0.008	0.398
Woburn	0.018	0.014

Irrigation demand

Results from the analysis of average annual irrigation demand are shown in Figure D-2. The weather generator results are within one 25 mm application (the depth of a typical single application) of the annual irrigation demand computed from the observed record at all the sites except Ringway, which recorded a difference of 35 mm (equivalent to 27% difference).

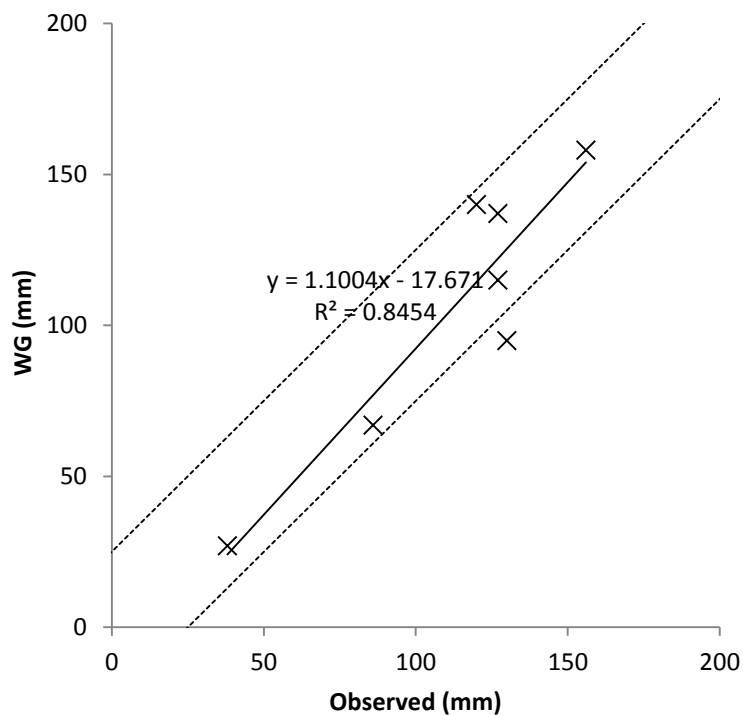


Figure D-2 Average annual irrigation demand for all seven sites modelled using the observed and weather generator datasets. Dotted lines indicate +/- 25mm error on observed baseline, Ringway is the only outstanding site. Best fit trend line is included.

Statistical analysis, using a combination of Man Whitney U-test (MWUt) and 2-sample T test (2Tt) showed that the observed and weather generator values for the average annual irrigation demand were not significantly different at any of the investigated sites (Table D-3). Significant differences were however recorded in the inter-annual standard deviation at two sites, Carlisle and Ringway.

Table D-3 Test for significant differences comparing observed and weather generator average annual irrigation demand and inter-annual standard deviation at the 95% confidence interval for all seven sites.

Site	Average annual irrigation demand		Inter-annual irrigation demand standard deviation	
	Statistical analysis	P-value	Statistical analysis	P-value
Brooms barn	2Tt	0.882	2Tt	0.809
Carlisle	2Tt	0.095	2Tt	0.015
Ringway	2Tt	0.063	2Tt	0.011
Shawbury	2Tt*	0.669	2Tt	0.291
Slaidburn	MWUt	0.499	MWUt	0.355
Terrington	MWUt	0.142	2Tt	0.092
Woburn	2Tt	0.557	2Tt	0.727

*Transformed data

The observed and weather generator annual irrigation demands, plotted against probability of non-exceedance, are shown in Figure D-3. It should be noted that the discrete depths of water applied (15 mm and 25 mm) accounts for the steps in the observed weather results, whereas these are smoothed out by the averaging of 300 sequences for the weather generator results.

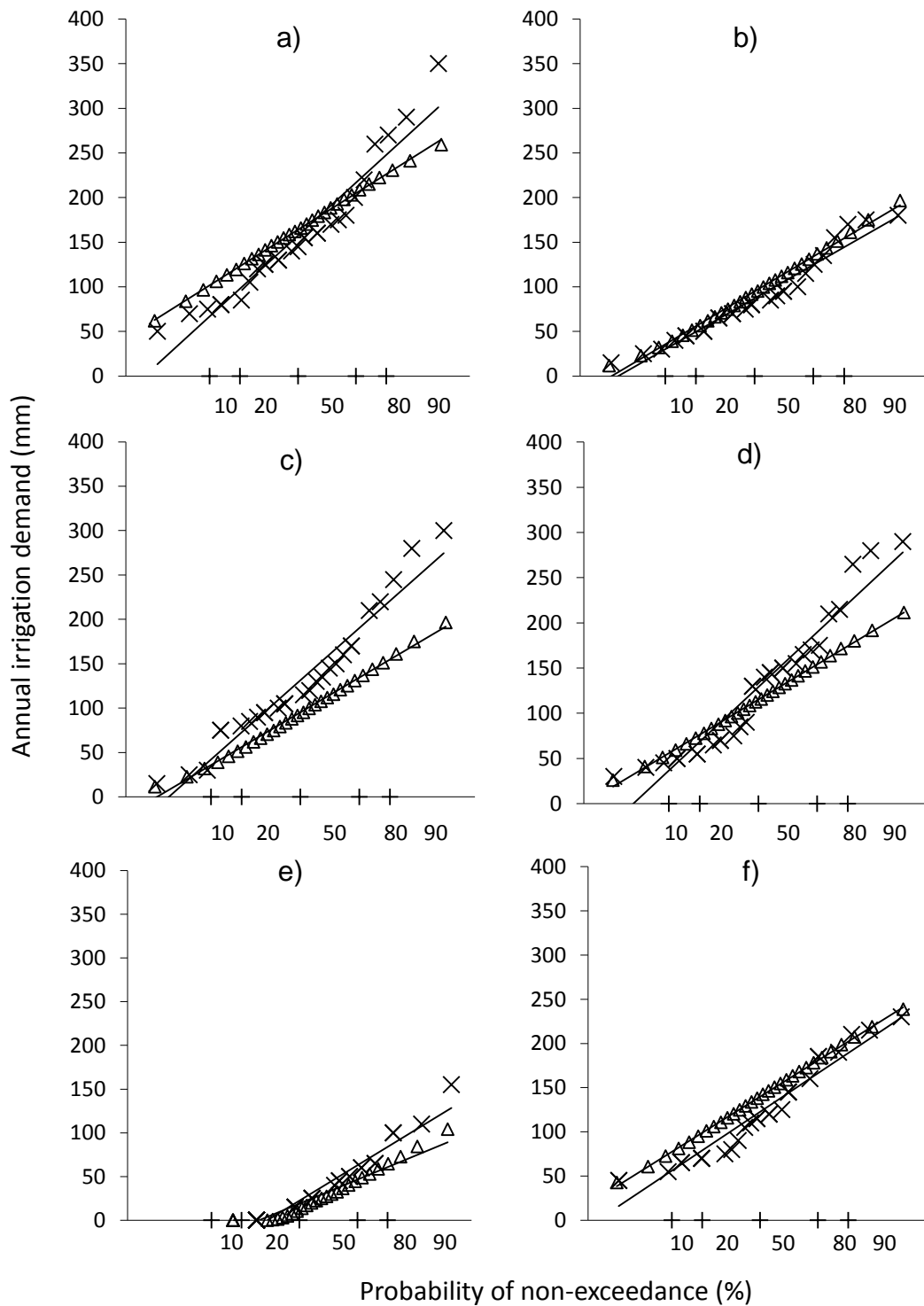


Figure D-3 Annual irrigation demand against probability of non-exceedance for the baseline period for Brooms barn (a), Carlisle (b), Ringway (c), Shawbury (d) Slaidburn (e) and Terrington (f) comparing results from observed (X) and weather generator datasets (Δ). Results for Woburn are shown in figure 5.

Hence the weather generator appears reasonably successful in modelling the annual irrigation demand in normal years, with the exception of at Ringway, which could be the result of an unusual micro-climate at this particular site. It underestimates the observed conditions during the driest years at the majority of the sites. This may reflect the occurrence of the extreme dry years 1975 and 1976 in the observed dataset. Even the most extreme results in the 300 sequences did not reach the values for these exceptionally dry years at all sites, for example at Woburn (Figure D-4).

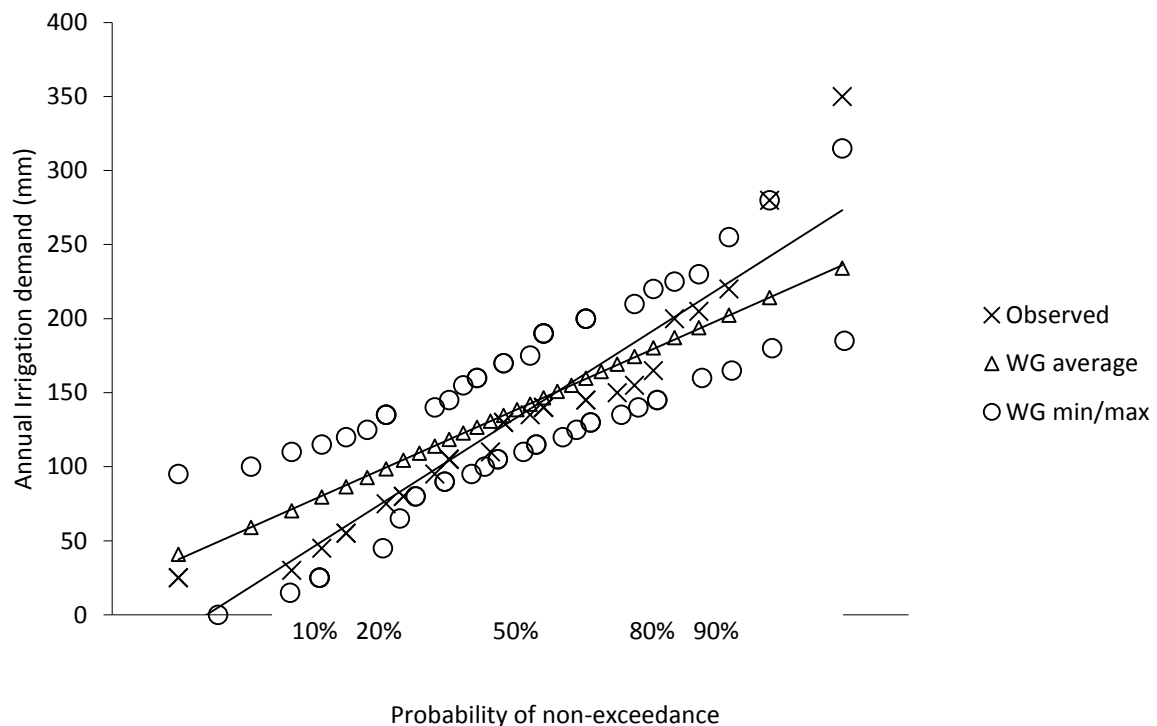


Figure D-4 Woburn annual irrigation demand against probability of non-exceedance for the baseline period 1961-1990 observed (X) and weather generator average (Δ) and weather generator max/min respectively. 80% represents the current best practice approach.

A design dry year for allocating agricultural water resources and designing irrigation systems and storage reservoirs in the UK is typically taken as one with an 80% probability of non-exceedance, roughly equivalent to the older concept of the “fourth driest year in five” (Weatherhead and Knox, 2000). The weather

generator was largely successful in replicating the observed dry year values (Table D-4). The average of the 300 weather sequences was within 25 mm at all but one of the sites, Ringway. The average weather generator value tended to be lower than the observed baseline value.

Table D-4 Design dry year (80% probability of non exceedance) irrigation demand (mm) for the seven sites for the baseline period, calculated using the observed and weather generator dataset respectively.

Site	Observed	80% probability of non-exceedance event		
		Weather generator (300 sequences)		
		Average	Range	Standard deviation
Brooms barn	196	198	165-236	12
Carlisle	121	99	71-131	11
Ringway	170	132	105-171	12
Shawbury	172	152	116-187	11
Slaidburn	61	50	25-86	10
Terrington	175	179	145-217	12
Woburn	157	176	141-212	12

The study used 300 sequences, based on the recommendations of UKCIP. Analysis showed that it is theoretically possible to use far fewer weather generator sequences and still remain confident that the average and design dry year values are reasonably reflective of the full population (Table D-5). For estimating annual irrigation demand with a 25 mm acceptable error - at the 95% confidence interval., required just 2 sequences at most sites, and only 1 at Slaidburn. Decreasing the acceptable error to 10 mm led to an increase to 4 sequences at most sites. Similar results were recorded with the 80% design dry year, with most sites requiring 2 sequences and 5 sequences respectively. Using the equation does require a degree of hindsight about the standard deviation, but this could be estimated using a simple model such as WaSim, before using a more complex crop model. However, there are limitations to the use of this equation, and it is strongly recommended that more sequences than these values are used to give confidence in the results.

Table D-5 Minimum number of weather generator sequences at the 95% confidence interval., generated using the standard deviation of 300 weather generator sequences and an error coefficient of 10 mm and 25 mm respectively.

Sample size (N0) Site	Average annual irrigation demand		80% percentile design dry year	
	Error coefficient (e)		Error coefficient (e)	
	10 mm	25 mm	10 mm	25 mm
Brooms barn	4	2	5	2
Carlisle	3	2	5	2
Ringway	4	2	5	2
Shawbury	4	2	5	2
Slaidburn	2	1	4	2
Terrington	4	2	5	2
Woburn	4	2	5	2

Conclusions

Findings of this study first demonstrated that the version 1 of the UKCP09 weather generator performed poorly when replicating observed precipitation and evapotranspiration, based on both recorded weather station and interpolated grid data. This was unexpected considering that the UKCP09 weather generator was originally calibrated on the Met Office's interpolated grid, itself created from the UK's weather station network. The weather generator was noticeably worse at reproducing observed evapotranspiration than precipitation, while both weather generator variables were generally closer to the point measurements compared to the interpolated grid.

Nevertheless, the study has demonstrated that the weather generator was reasonably successful at replicating the average annual irrigation demand, the annual variation in observed irrigation demand and the design dry year demand (based on the 80% probability of non-exceedance event). The weather generator was less successful at replicating the driest years in the recorded dataset, but these were exceptionally dry years. Previous studies have identified similar limitations in the weather generator's ability to reproduce extreme events. The

UKCP09 weather generator is unable to recreate blocking regimes effectively, which themselves can lead to extended heat waves, exceptionally cold winters and droughts with obvious implications for irrigation demand modelling (Jones et al., 2009). While improvements have been made, large return period events should still be treated with caution (Harris et al., 2012). Its limited ability to recreate extreme events is unlikely to impact the decision making process in the irrigation context, but could be more significant in other applications. This study did not consider whether the UKCP09 weather generator could successfully reproduce observed day-to-day operations at field level (i.e. when and how often to undertake irrigation). However, given the highly variable day-to-day climate in the UK it is very unlikely that the UKCP09 weather generator would be capable of doing so, though further work is recommended to test the validity of this assumption. In addition, further work is recommended to establish whether or not later versions of the UKCP09 weather generator improve the reproducibility of observed conditions.

The findings of this study have demonstrated the potential value of the weather generator as an alternative and potentially more accessible source of baseline daily data for irrigation and water resource planning, but highlight the need for caution. The generated climate data can be downloaded from UKCP09 in the absence of sufficient baseline data, and is particularly useful for sites where data is considered to be poor quality or suspect. The weather generator output also contains additional probabilistic climate information, represented by the variation between sequences in the average annual irrigation demand and 80% design dry year. This data is not particularly useful for analysing irrigation demand during the baseline period but would be directly applicable to modelling the future (Green and Weatherhead, 2014b), giving some (partial) indication of climate variability and uncertainty. In addition, future studies using the UKCP09 weather generator (such as Green and Weatherhead, 2014b) can be considered more robust, at least at these particular sites, now that it has been demonstrated that the weather generator can effectively recreate the observed baseline demands.

The study has also demonstrated that it is feasible to use fewer weather generator sequences and still remain confident that any subsequent conclusions drawn from the design dry year are reflective of a much larger sample, although any underlying differences with observed values will still remain. While determining the minimum number of sequences does require some degree of hindsight about the standard deviation, and is unnecessary for relatively simple models like WASIM, this should prove of interest to modellers using more complex models that cannot process and subsequently interpret the large number of weather generator sequences used in this study.

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Appendix E The application of probabilistic climate change projections: A comparison of methods of handling uncertainty applied to UK reservoir design

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Abstract

Climate projections are increasingly being presented in terms of uncertainties and probability distributions rather than median or “most-likely” values. The current national UK climate change projections, UKCP09, provide 10,000 probabilistic projections and 11 spatially coherent projections (11SCP) for three future emission scenarios. In contrast, previous iterations such as UKCIP02 provided only a single “most-likely” (deterministic) projection for each. This move from deterministic to probabilistic methods of communicating climate change information, whilst increasing the wealth of the data, complicates the process of adaptation planning by communicating extra uncertainty to the public and decision makers.

This paper examines the application of probabilistic climate change projections and explores the impact of uncertainty on decision making using a case study of irrigation reservoir design at three sites in the UK. The implications of subsampling the probabilistic projections using both simple random and Latin-hypercube sampling were also explored.

The study found that the choice of dataset had a much larger impact on irrigation reservoir design compared to emission uncertainty. The study confirmed the dangers of inadequate sample size, particularly when applying decision criteria based on extreme events, and found that more advanced stratified sampling techniques did not noticeably improve the reproducibility of decision outcomes.

Keywords: Probabilistic, deterministic, decision making under uncertainty, UKCP09, WaSim, adaptation planning

Introduction

In the UK, approximately 150,000 hectares of agricultural land are irrigated (Knox et al., 2010). In parts of the UK during a dry year, supplemental irrigation is essential for growing high quality produce, most notably potatoes. However, increasing demand, climate change and the need to balance environmental demands are now adversely affecting the availability of water for irrigation (Weatherhead et al., 2008). Farmers with access to a winter-filled reservoir can ensure the environmental impact of irrigation abstraction during summer months, when water resources are most constrained, are reduced (Weatherhead et al., 2008).

Irrigation reservoirs, like much of the UK's water infrastructure were originally designed on the assumption that the climate in which it was built would endure for its lifetime; due to climate change this is no longer the case (Gleick, 2011). As a result, climate change projections are increasingly being used to test the performance of existing assets as well as support the design of new assets which will be robust to climate change (Harris et al., 2012; Anderson and Bows, 2011; Fung et al., 2011; Sanderson et al., 2011; Green and Weatherhead, 2014c). This approach is commonly referred to as scenario-led adaptation and is the focus of this research; readers should be aware there are other approaches to adaptation including vulnerability (or bottom-up) and hybrids thereof, the merits of which are discussed elsewhere and in greater detail (Wilby and Dessai, 2010; Brown and Wilby, 2012). Scenario-led adaptation uses downscaled regional-scale climate projections to inform adaptation plans designed to maximise potential benefits and/or minimise potential risks (Wilby and Dessai, 2010). Scenario-led adaptation is gradually gaining more traction within the scientific community; although practical uptake is limited to some extent by the financial and technical capacity of the individuals undertaking adaptation, their risk appetite, the availability of high quality downscaled climate change information and the type of adaptation options being considered (Adger et al., 2005; Dessai et al., 2005).

Decision makers are increasingly looking to scientists for information about the likelihood of future climate change. Traditionally, science has proved invaluable

to decision makers, either by providing accurate predictions or by enabling technological advancements which have enabled decision makers to 'steer' the future toward desired outcomes (Dessai et al., 2009). Unfortunately, there are many examples, of which climate change is an example, where the science has not been as forthcoming as decision makers had hoped (Millner, 2012). Scientists, correctly, emphasise the uncertainties, while decision makers seek a clear picture. As a result, a large disparity has begun to emerge between what decision makers want and what scientists can reasonably provide.

Recent advances in computational power have allowed for partial quantification of model uncertainty including perturbed physics ensembles (Stainforth et al., 2005), multi-model ensembles (Tebaldi and Knutti, 2007) and advanced statistical techniques (Rougier, 2007) on which the current generation of national UK climate change projections, termed UKCP09, are founded.

In recent years, a change from deterministic to probabilistic methods of communicating climate change information and uncertainty has been observed, though how the latter should be interpreted is an area of continuing debate (Stainforth et al., 2007). Expressing climate change as a range of potential outcomes as opposed to a single value in itself increases the complexity. The move from deterministic methods of communicating climate change information (e.g. UKCIP02) to probabilistic methods (e.g. UKCP09) may be viewed as a 'conceptual leap' and has forced many decision makers to reassess how they use climate change information to inform policy (Harris et al., 2012; Weaver et al., 2013).

In the UK, the current suite of national suite of climate change projections is UKCP09 (Murphy et al., 2009). UKCP09 used advanced statistical methods to generate probabilistic projections of future climate change and thereby explore the wider uncertainties in climate system processes. Probabilistic climate projections are provided at a 25km scale resolution generated from a perturbed ensemble experiment using the HadSM3 Global climate model (GCM) (Murphy et al., 2009). Some 10,000 probabilistic monthly change factors are available for a 25km grid covering the whole of the UK, for three different greenhouse gases

emission scenarios (low, medium and high) for seven 30 year time-slices (2020s, 2030s, 2040s, 2050s, 2060s, 2070s and 2080s respectively). Future climate change is thus expressed as a large range of potential outcomes as opposed to a single 'most likely' projection (Dessai et al., 2009).

In addition to 10,000 probabilistic projections, 11 spatially coherent projections (11SCP) are available via the UKCP09 user interface. The 11SCP were created by applying scaling factors to the 11-member regional climate models (11RCM) with the aim of incorporating the wider uncertainties considered by UKCP09. Unlike the 10,000 probabilistic projections, the 11SCP are spatially and temporally consistent across the grid. The 11SCP should be used wherever the decision maker is considering impacts derived from more than one grid square in a spatially coherent way, e.g. catchment runoff, or wants to explore some of the uncertainty associated with UKCP09 (the 11SCP consider a much wider range of uncertainty compared to the 11RCM, although not as much as the 10,000 probabilistic projections). However while the 11SCP are considered to be equiprobable, the projections are not probabilistic in nature; e.g. they do not consider the structural uncertainty in the atmospheric processes, uncertainty arising from the carbon and sulphur cycle or ocean physics. UKCIP have been clear to stress that the 11SCP are not a replacement for the probabilistic projections, despite this, some users may purposely use them, even for single grid squares, because the resources required to process and interpret the outputs from the 11SCP are much smaller.

As previously suggested, one of the key challenges facing users of UKCP09 is the sheer number of climate change projections that are provided. UK Climate Impacts Programme (UKCIP) recommends decision makers use a minimum of 100 climate change projections in order to preserve the probabilistic characteristics of the underlying projections (Christierson et al., 2012). Of course a sample this large may still be beyond the capabilities of many complex models, in particularly national scale models (Christierson et al., 2012) and computationally demanding models such as DSSAT (Daccache et al., 2011). As a result, it is often necessary to sub-sample the 10,000 projections (alternatively,

a rapid assessment model can be used though these are discussed elsewhere and in greater detail, see Kwakkel et al., (2012), Haasnoot et al., (2012). The design and complexity of these sampling methods will depend on both the availability of resources and technical expertise to the decision maker in question.

The size of these sub-samples and choice of sampling methodology are particularly important. Basing decisions on a single or small subset of projections can result in maladaptation, if events occur which are outside the range described by that subset of projections. Using a wide range of projections can lead to increased adaptive capacity, although it is not guaranteed to be more successful, especially if the “real” future climate is not expressed by any single projection within the available projections (Dessai and Hulme, 2007). Furthermore, if the potential climate change impacts are diverse and the projections too numerous or difficult to interpret, the identification of suitable adaptation measures may become too complex and no action may be taken, with potentially serious consequences.

Latin hypercube sampling (LHS) (McKay et al., 1979) has previously been shown to be an effective tool for sub-sampling the UKCP09 dataset (Christierson et al., 2012). In two dimensions, a Latin hypercube can be represented by a simple grid, with one climate variable represented by a row and the other climate variable a column. A Latin hypercube with more dimensions can be considered the generalisation of this concept. This study utilises two types of Latin hypercube sampling, specifically optimum and Maximin. Optimum LHS uses a columnwise-pairwise (CP) algorithm to generate an optimal design using an S optimality criterion (Liefvendahl and Stocki, 2006). An S optimality criterion seeks to maximise the average distance between design points (or projections) to all other points in the state space (Stocki, 2005). In contrast, Maximin LHS maximizes the minimum distance between design points, this ensures the points out are spread out across the state space (Stein, 1987).

Climate projections from UKCP09 can be directly imported into soil water balance models such as WaSim (Hess and Counsell, 2000), freely available via the Cranfield University website, to model the irrigation demand of various crops. This

data, combined with cost and benefit information has been used for example to inform the optimum capacity of a reservoir required to meet future irrigation demands. WaSim simulates inflow (i.e. infiltration) and outflow (i.e. evapotranspiration and drainage) and storage of soil water in response to climate, irrigation and drainage (Depeweg and Fabiola Otero, 2004). WaSim has proven invaluable in a range of previous studies including determining irrigation requirements; optimising water management, assessing the performance of sub-surface drainage systems and studying the effects of climate change on water resources (Depeweg and Fabiola Otero, 2004; Hirekhan et al., 2007; Warren and Holman, 2012).

WaSim requires rainfall and evapotranspiration data, the latter can be estimated using Penman-Monteith (used here), FAO Modified-Penman or Penman methods (Monteith, 1965). Guidance values covering crop development and root depths are provided for several crops within WaSim, enabling up to three crops to be combined in a cropping pattern (Hess and Counsell, 2000). Irrigation schedules may be set up as either calendar or rule-based. Calendar schedules assume a fixed irrigation date, whereas rule based scheduling, used here, divides the cropping season into a series of irrigation and non-irrigation periods governing the frequency and volume of irrigation required.

In the field of irrigated agriculture, decision makers have typically relied on the design dry year approach for estimating the volume of irrigation required. A design dry year is defined in the UK as a year with an 80% probability of non-exceedance (roughly equivalent to the older “fourth driest year in five”). This industry “rule-of-thumb” forms the basis of many asset design and water allocation decisions in the field of irrigated agriculture (Weatherhead and Knox, 2000). However, recent studies suggest that the current 80% probability of non-exceedance approach may risk maladaptation (Green and Weatherhead, 2014d).

Alternative decision criteria may be sought which dispense with probability all together (Ranger et al., 2010). These criteria are commonly used to support decision making under uncertainty (i.e. in situations where no information of event likelihood exists) (Ranger et al., 2010; Dessai et al., 2009). These criteria include

Laplace's criterion (Laplace 1825), Wald's Maximin criterion (Wald, 1945), Maximax criterion, Hurwicz's realism criterion (Hurwicz, 1951), and Savage's Minimax regret criterion (Savage, 1951). For the purpose of this study it was assumed that the decision maker would use Laplace (in line with emerging guidelines, see for example Environment Agency, (2013), though the other decision criteria (i.e. Maximin, Maximin, Minimax regret and Hurwicz's criteria) are presented for completeness. Laplace's criterion is based on the premise of symmetry (Ranger et al., 2010); each potential environmental state (i.e. each climate change projection) is considered to be equi-probable in the absence of prior knowledge. The average expected payoff for each option (i.e. reservoir capacity) is calculated using all the states (i.e. climate projections); for Laplace, the option providing the largest average payoff is considered the design capacity. Maximin identifies the best option as the option which provides the largest expected outcome from the worst possible state. In contrast, Maximax identifies the best option as the option providing the largest outcome from the best possible state. The best option under Hurwicz's criterion is calculated using a weighted average of Maximin and Maximax (with the weighting defined by α , representing the optimism of the decision maker). Minimax regret identifies the option with the smallest regret, representing the difference between the best and worst possible outcomes across all states. For a detailed explanation covering the methods used to generate all of the criteria readers are directed to (Sniedovich, 2007), (Ranger et al., 2010) or more recently (Green and Weatherhead, 2014c).

Aim

The aim of this study was to examine the implications of different ways of using probabilistic climate change projections and explore the impact of uncertainty on decision making, using a case study of irrigation reservoir design at three sites in the UK on the basis of the 2050s low, medium and high emission scenarios. It critically compares the optimum reservoir sizes obtained using the median or "most likely" projection and design reservoir capacities using the 11SCP projections and the 10,000 probabilistic projections, under various decision making criteria. It then critically compares applying simple random, Optimal and

Maximin Latin hyper cube methods of sub-sampling the 10,000 probabilistic projections.

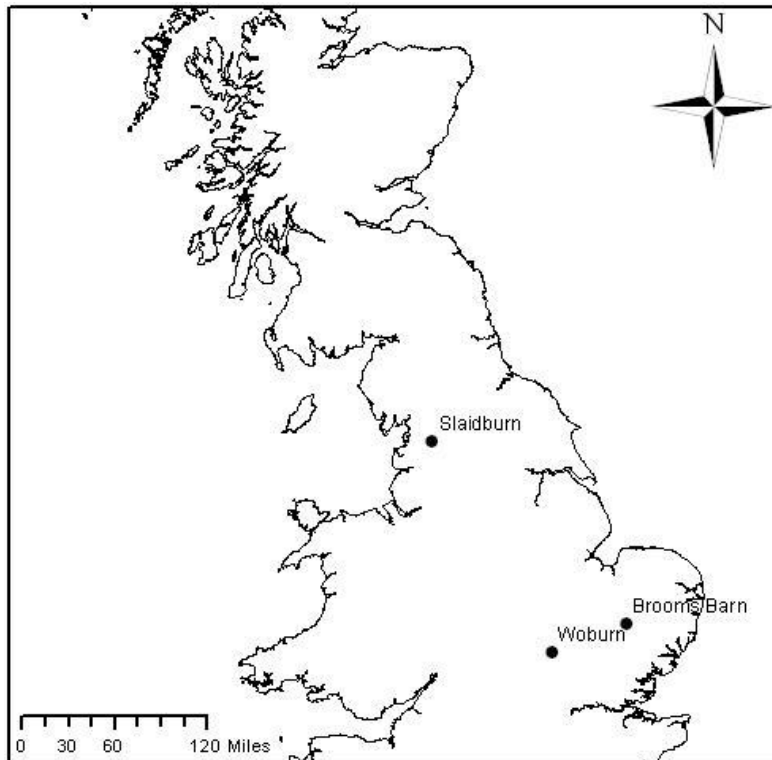
Methodology

A series of irrigation reservoirs were designed using projections derived from the UKCP09 low, medium and high emission scenarios for the 2050s for three sites in the UK. Design reservoir capacities were identified using Laplace, Maximin, Maximax, Minimax regret and Hurwicz's criterion using the complete probabilistic dataset (i.e. all 10,000 projections), 11SCP and various sub-samples of the complete probabilistic dataset using different sampling techniques.

Brooms Barn is located in the county of Suffolk, near Bury St Edmunds, approximately 30km east of Cambridge and is the driest of the investigated sites. Slaidburn is located in the district of Lancashire, approximately 60km north-west of Leeds and is the wettest site with an average annual rainfall of 1515 mm for the baseline period. Lastly, Woburn is situated in the county of Bedfordshire, 50km north-west of London and is marginally wetter than Brooms barn but with slightly lower annual evapotranspiration. Observed climate data was extracted for the baseline period from the weather station at each site. Additional hydroclimatology data for the baseline period (1961-1990) is shown in Table E-1.

Table E-1 Weather station sites and records used.

Station	Lat.	Long.	Elevation (m AOD)	Average annual (1961-1990)		Data	
				Rain (mm)	ETo (mm)	From	To
Brooms Barn	52.260	0.567	75	588	585	1964	1990
Slaidburn	53.987	-2.433	192	1515	487	1961	1990
Woburn	52.014	-0.595	89	632	564	1961	1990



Readers are directed to (Green and Weatherhead, 2014b) for a detailed explanation of the methods used to generate the future climate projections used in this study. In summary, observed daily weather data was extracted from a weather station at each site Table E-1. All 10,000 sets of monthly change factors were downloaded from UKCP09 for the 25km grid square overlying each weather station for the 2050s time slice (i.e. 2040-2069). These were used to generate evapotranspiration change factors using Penman-Monteith (Monteith, 1965). The monthly precipitation and evapotranspiration change factors were then used to perturb the observed daily weather series, producing 10,000 future daily projections for each site.

WaSim was used to model the annual irrigation water use at each site. In its basic format WaSim is not capable of processing multiple climate files succinctly, so a modified version was developed and employed for this study to speed up data processing. This modified version was designed to read in multiple climate files and output a single .csv file containing the daily irrigation demand for each projection. The annual water use of a potato crop was calculated for each year in the 10,000 x 30 year sequences from the probabilistic projections for each site

and emission scenario. Typical costs and benefits for clay agricultural reservoirs were obtained from a concurrent study (Green and Weatherhead, 2014b). The net present values (NPV) of a range of reservoir sizes, with usable storage capacities equivalent from 0 to 1000mm depth over the area irrigated (i.e. 0 to 10,000 m³.ha⁻¹), were then calculated for each of the 10,000 projections (see Figure E-1 for an overview of the methodology).

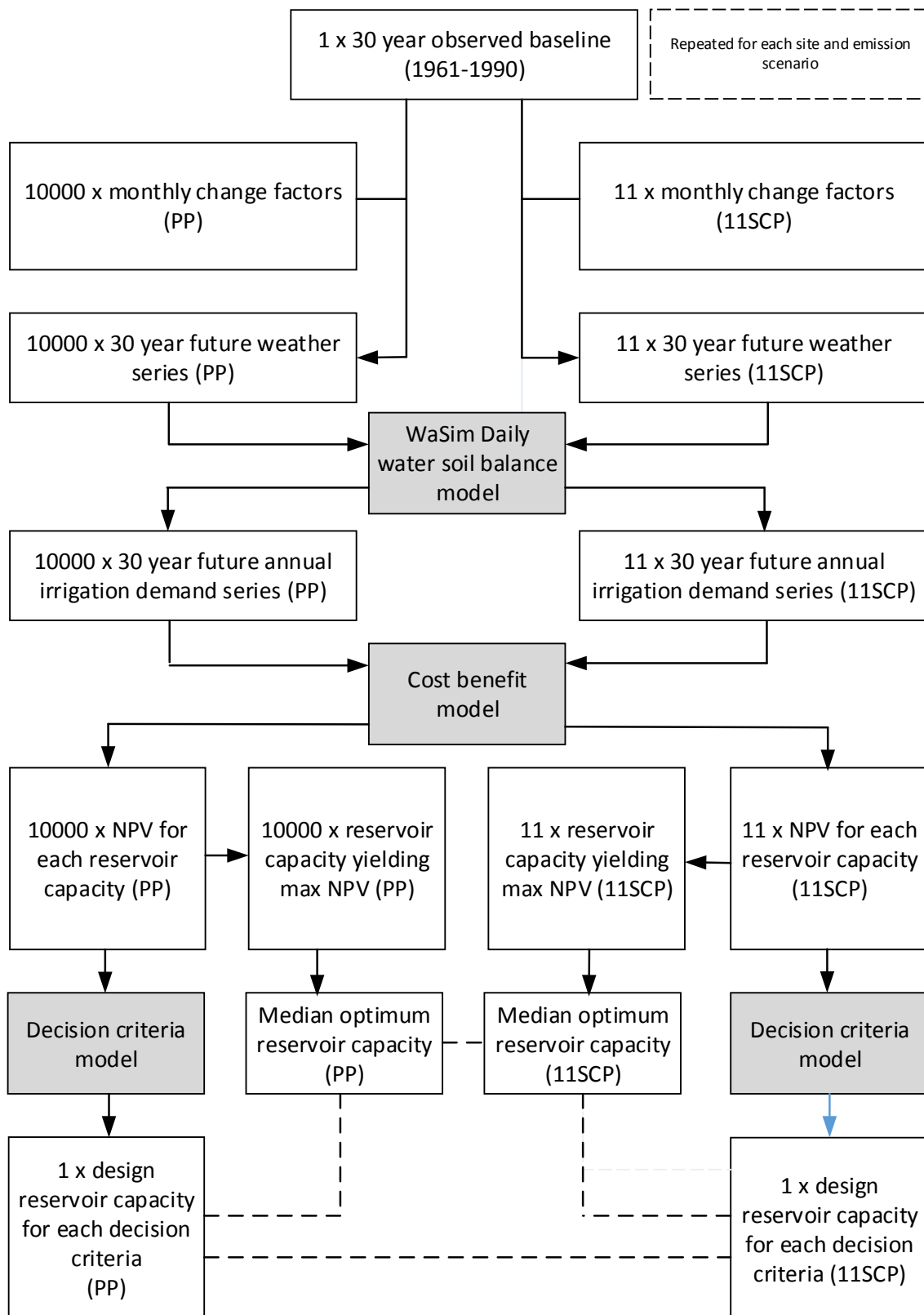


Figure E-1 Methodology schematic flow chart (dotted line shows comparison made).

Laplace and the other decision criteria were then used to select the design reservoir capacities across all 10000 probabilistic projections (i.e. S1 to S10000), as shown in Table E-2. For example, for Laplace this was the capacity providing the maximum NPV averaged across all of the 10,000 probabilistic projections, whereas for Maximin this was the capacity providing the maximum NPV based on the worst case of all the 10,000 probabilistic projections. Where the result was found to be negative, the capacity was set at zero i.e. it was assumed no reservoir would be built.

Table E-2 Simplified example of calculations using the decision criteria and median reservoir capacity (not actual data).

Option (reservoir capacity)	State				Outcome/Decision criteria				
	S1	S2	S3	...etc	Average (Laplace)	Minimum (Maximin)	Maximum (Maximax)	Regret (Minimax regret)	Weighted average max:min (Hurwicz)
A	10	20	50	100	45	10	100	900	55
B	2	3	3	100	252✓	2	1000✓	199✓	501✓
C	20	20	20	202	201	200✓	202	798	201
D	10	11	12	410	185	100	410	590	255
... etc									
Highest NPV	20	20	20	100	Decision design outcome (✓)				
“Optimum ” option	C	C	C	B	B	C	B	B	B
Median	C								

The whole process was then repeated for the 11SCP dataset and the results compared.

To examine the implications of different ways of using probabilistic climate change projections and explore the impact of uncertainty on decision making

associated with moving from a single deterministic projection to probabilistic projections, it is of course necessary to know the single projection that would have been used if only one projection was provided. However, in the case of UKCP09, no such single “most-likely” projection exists when dealing with multiple climate parameters; each of the 10000 projections is considered to be equally likely (UK Climate Impacts Programme, 2014). It would be tempting, but potentially misleading, to try to select one with median temperature, median rainfall, etc.; however, such a combination could actually be unlikely. Selecting the most-likely projection within a single metric would require a (partly) arbitrary choice; using a different metric would probably lead to a different projection.

A comparison against the state (i.e. projection) with the median optimum outcome was used here, though of course identifying that state required all the projections to be modelled first. The reservoir capacity providing the maximum NPV was identified for each projection and the median value (i.e. the capacity which has an equal probability of being exceeded and not being exceeded across all 10,000 scenarios) selected. However it is important to stress that the projection underpinning this median optimum outcome or reservoir capacity is not necessarily the median climate projection; in a non-linear system using the average or median values of the individual climate parameters does not necessarily give the average or median impact.

The differences in reservoir capacities between using all of the probabilistic projections and all of the 11SCP, using Laplace and other decision criteria, and the median optimum reservoir capacity were then assessed.

This study considered two sources of uncertainty; 1) uncertainty attributed to differences between the 11SCP and 10,000 probabilistic projections and 2) emission scenario uncertainty. The chosen methodology enabled both sources of uncertainty to be simultaneously compared whilst providing an insight into the impact of uncertainty to decision making for irrigation reservoir design. Uncertainty associated with the 11SCP and 10,000 probabilistic projections was assessed by comparing differences between the median optimum reservoir capacities (i.e. the “most likely” outcomes) and the range of outcomes of both

datasets (represented by box and whisker plots). The impact of emission scenario uncertainty was assessed by comparing the differences in reservoir capacities between the low, medium and high emission scenarios. The impact of the choice of decision criteria was also assessed by comparing the reservoir capacities based on different decision criteria with the median optimum reservoir capacity representing the “most likely” outcome.

In order to compare the success of alternative sampling methods, simple random sampling and two variants of Latin hypercube sampling (optimum and Maximin respectively) were used to sub-sample the probabilistic dataset. Sub-samples created using these methods were compared to each other and the complete dataset in terms of the design reservoir capacity based on Laplace and the other decision criteria. The Latin hypercube method presented here sampled 30 future projections from the 10,000 available for the 2050s using six dimensions to stratify the probabilistic dataset. These six dimensions consisted of the monthly precipitation and evapotranspiration change factors for June, July and August (the three main irrigation months). All six dimensions were tested for inter-correlation prior to undertaking Latin hypercube sampling. Thirty climate projections were used, as this provided a balance between sampling accuracy and efficiency and was considered to be representative of real world practice. Each 30 projection Latin hypercube sample was then compared to the complete dataset as well as the simple random sample (also consisting of 30 projections) by identifying the design reservoir capacity on the basis of each decision criteria. Each of the projections within the simple random sample was randomly selected using only the projection number.

Results

The design reservoir capacities calculated across the 10,000 probabilistic projections and across the 11SCP were compared first, using each of the decision criteria in turn. Design reservoir capacities using Laplace (summarised in Table E-3) show small differences (<8%) between the emission scenarios, but much larger differences between using the probabilistic projections and 11SCP (10 to 25%, depending on the site and emission scenario). This suggests that the

uncertainty considered by the probabilistic projections (and that is absent from the 11SCP) has a much larger impact on irrigation reservoir design compared to the choice of emission scenario. This agrees with studies by who found that the choice of emission scenarios had a comparable small impact on future water shortages in the public water supply sector. In addition, the results show that using the probabilistic projections consistently resulted in building a bigger reservoir compared to using the 11SCP, regardless of the site and emission scenario used. In contrast, a previous study by (Kay and Jones, 2012) found that the median of the probabilistic projections and 11SCP were generally in agreement regarding changes in flood frequency. Similar results were obtained using the other decision criteria, with the exception of Maximin which suggested building a much smaller reservoir when using the probabilistic projections.

Table E-3 Design reservoir capacities (mm) calculated using Laplace across all of the 10,000 probabilistic projections (PP) versus the 11 SCPs, for Brooms Barn, Slaidburn and Woburn, for the 2050s low, medium and high emission scenario.

Decision criteria	Site	Brooms barn			Slaidburn			Woburn		
	Emission	L	M	H	L	M	H	L	M	H
Laplace	PP	390	410	400	0	0	0	360	380	390
	11SCP	350	350	360	0	0	0	280	280	290

The ranges of reservoir capacities, providing the maximum NPV for each of the projections for each dataset were then compared. Box and whisker plots showing the min, 25th percentile, median, 75th percentile and max reservoir capacities for Brooms Barn are shown in Figure E-2. The probabilistic projections gave a much wider interquartile range compared to the 11SCP, and at Brooms Barn and Woburn the median optimum reservoir capacities were larger compared to the 11SCP. This result, consistent with the previous findings, suggest that the choice of dataset (and the range of uncertainty it considers) has a much larger impact on the decision outcome compared to the choice of emission scenario.

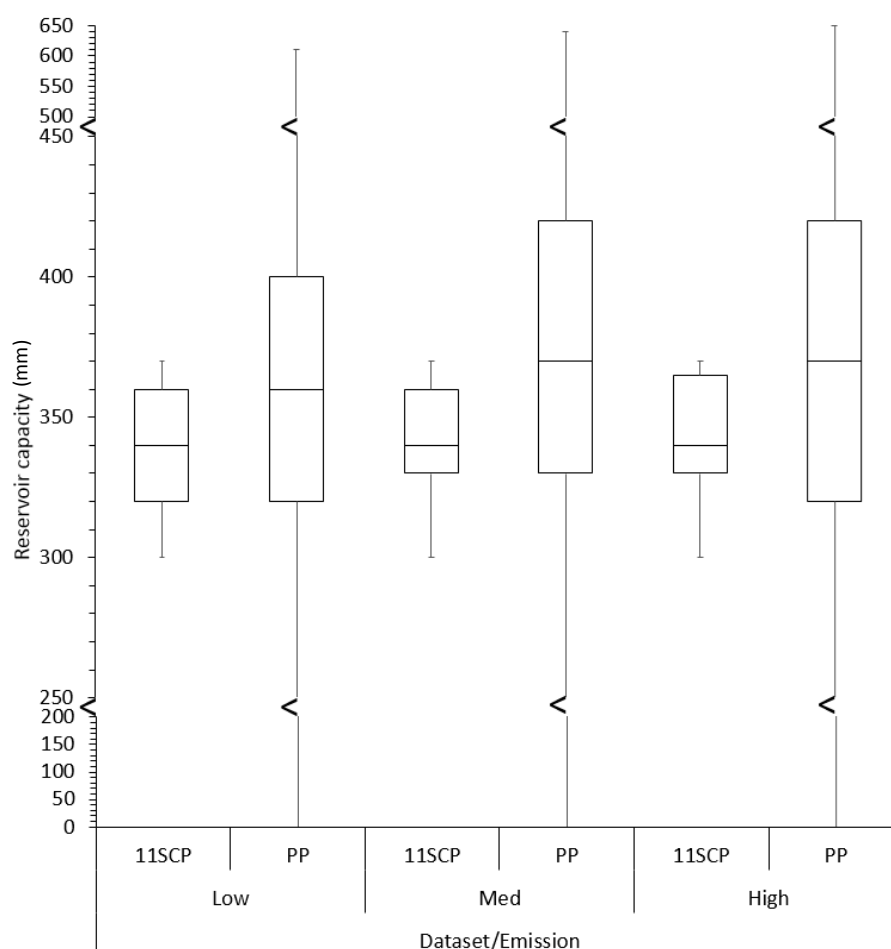


Figure E-2 Median optimum reservoir capacities (mm) using each of the 10,000 probabilistic projections and each of the 11SCP projections individually, for Brooms Barns. Plots show lowest, 25th percentile, median, 75th percentile and highest optimum reservoir capacity for each dataset.

Next, the median optimum capacities of both datasets, representing the “most-likely” decision outcomes, were compared to the design reservoir capacities on the basis of each decision criteria across all of the probabilistic projections and across all of the 11SCP (Table E-4).

Table E-4 Reservoir capacities (mm) calculated using median “most likely” decision outcome and compared to the design reservoir capacities calculated using Laplace and other decision criteria using the complete probabilistic dataset

(PP) and 11SCP for all three sites. Hurwicz's criterion calculated using coefficient of optimism $\alpha=0.5$.

Decision criteria	Site	Brooms barn			Slaidburn			Woburn		
	Emission	L	M	H	L	M	H	L	M	H
Median optimum reservoir capacity	PP	360	370	370	0	0	0	310	320	330
	11SCP	340	340	340	0	0	0	280	280	270
Laplace	PP	390	410	400	0	0	0	360	380	390
	11SCP	350	350	360	0	0	0	280	280	290
Maximin	PP	0	0	0	0	0	0	0	0	0
	11SCP	300	300	300	0	0	0	250	250	250
Maximax	PP	600	620	650	280	310	330	530	580	620
	11SCP	370	370	370	0	190	200	300	300	310
Minimax regret	PP	420	450	430	100	120	140	380	420	440
	11SCP	350	350	350	0	0	0	280	280	290
Hurwicz	PP	560	590	600	270	300	300	510	540	570
	11SCP	370	370	370	0	0	0	290	280	290

It is clear (Table E-4) that decision outcomes resulting from an individual who considers themselves risk neutral (i.e. someone who would typically use Laplace) would not be substantially different regardless of whether the “most likely” projection was used instead of the complete dataset, given the comparably small differences (0-15%) between the reservoir capacities obtained using Laplace and the median optimum reservoir capacities at all the sites investigated. Where reservoirs were indicated, the design capacities using Laplace across the dataset were higher than using the median values, and the capacities from using the full probabilistic dataset were higher than using the 11SCP dataset.

In contrast, the differences between datasets when using the other decision criteria were much larger and far more variable. The difference between the probabilistic projections and median optimum reservoir capacity were also generally larger than the difference between the 11SCP and the median optimum reservoir capacity. This result can be largely attributed to the wider range of

projections (and uncertainty) considered by the probabilistic projections which differ substantially in their decision outcomes. At Slaidburn, the low annual irrigation demand typically favoured taking no action meaning the differences between the probabilistic projections and median optimum reservoir capacity tended to be large regardless of the decision criteria or dataset used.

When used with the complete probabilistic dataset certain decision criteria such as Maximax and Maximin resulted in very extreme decision outcomes such as taking no action or building very large reservoirs. Sub-samples of the probabilistic projections were taken and the design reservoir capacities obtained using different decision criteria were compared with the results obtained using the complete probabilistic dataset. Certain decision criteria and their associated outcomes were successfully reproduced from sub-sampling while others including Maximin and Maximax were not. The percentage difference between the design reservoir capacities calculated using the complete probabilistic dataset and the average of 30 sub-samples (each consisting of 30 projections) for each decision criteria are shown in Figure E-3.

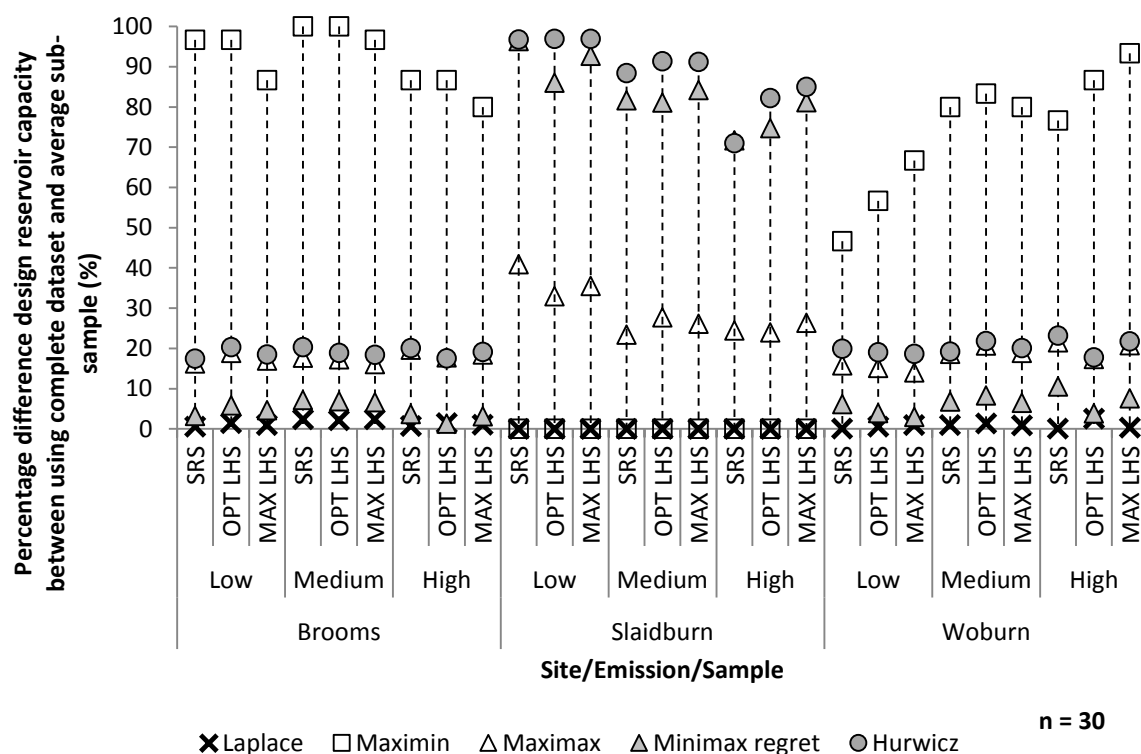


Figure E-3 Design reservoir capacity percentage differences using various decision criteria at Brooms Barn, Slaidburn and Woburn and different emission scenarios with selected sampling methods. Percentage difference represents the difference in design reservoir capacity from using the complete dataset to the average of 30 sub-samples (each consisting of 30 projections). Hurwicz's criterion calculated using coefficient of optimism $\alpha=0.5$.

Simple random sampling, optimum LHS and Maximin LHS performed comparably. (Christierson et al., 2012) previously suggested that LHS is an appropriate sampling approach for use with the probabilistic dataset. However, on the basis of these results it did not noticeably improve the “reproducibility” of the design reservoir capacities from the sub-samples (i.e. the percentage differences between the sub-samples and the complete probabilistic dataset did not vary greatly between sampling methods). All three sampling approaches yielded similar decision outcomes to each other, regardless of the decision criteria and site used. The number of projections contained within each sample (i.e. 30) was purposely designed to be representative of real-world practice;

further work using much large sample sizes is recommended, although whether this would be representative of practical real-world application is open to debate.

Sub-sampling highlighted the shortcomings of some of the decision methods. Design reservoir capacities calculated using Maximin, Maximax and Hurwicz's criterion were poorly reproduced from sub-sampling (Figure E-3). Similarly, Minimax regret was poorly reproduced at Slaidburn, however at Brooms Barn and Woburn the design reservoir capacity was reproduced reasonably well from sub-sampling, evident from the small percentage differences (Figure E-3). The decision outcome associated with Laplace, consistent with previous findings, was reproduced well from sub-sampling. In addition, unlike the other decision criteria, the difference between Laplace's design reservoir capacities using the complete probabilistic dataset and sub-samples was not affected by the site or emission scenario.

Discussion

Climate change uncertainty abounds as a result of epistemic and aleatory uncertainty. Uncertainties stemming from a lack of knowledge (e.g. cloud physics), randomness (e.g. chaotic nature of the climate system) and the result of future anthropogenic activity, whose effects may be far reaching and span many decades, but which are very much uncertain (e.g. greenhouse gas emissions, economic development, population growth etc) ((Dessai et al., 2009)). It is long been argued that effective adaptation necessitates an understanding of the uncertainty and is dependent on the availability of and access to accurate and precise climate change information (Cooper, 1977; Hickox and Nichols, 2003; Kelly, 1979; Murphy et al., 2004). Partial quantification of uncertainty has been attempted in recent years, although is an area of continual debate and development (Rougier, 2007; Tebaldi and Knutti, 2007; Stainforth et al., 2005)

Despite the seemingly irreducible uncertainty, decision makers still need to, and regularly do, make decisions without having access to accurate predictions. Various criteria and methods are available to assist them in doing so, the majority of which provide justifiable results in the absence of accurate and precise projections (Dessai et al., 2009; Polasky et al., 2011). These criteria and methods

typically work by identifying strategies that perform reasonably well over a wide range of future states at the expense of some loss of optimum performance.

It has previously been suggested that current decision criteria are applicable to adaptation planning (Ranger et al., 2010; Dessai et al., 2009; Polasky et al., 2011). At the time of writing, climate change impact assessments using UKCP09 are beginning to emerge, particularly within the building sector (Hanby and Smith, 2012; Williams et al., 2012). Despite growing awareness on the need for adaptation, practical examples of adaptation using current decision criteria appear lacking despite receiving renewed interest in recent years (Polasky et al., 2011).

Certain decision criteria are calculated using a single projection; it is these methods that were generally poorly reproduced from sub-samples of the complete probabilistic dataset. Given the sensitive nature of the design reservoir capacities to extreme projections it is not surprising that some sampling approaches appear inadequate when used in combination with these decision criteria. This result should serve as a warning for users of certain decision criteria with sub-samples of the probabilistic dataset (as opposed to a reason for inaction). None of the sampling approaches considered here, performed ideally. However, the alternative would require each of 10,000 projections to be modelled and the sampling strategy constructed in such a way as to ensure reasonable coverage of the samples in the state space. Unfortunately, such an approach is rarely feasible in practice due to the non-linear nature of climate variables and impacts and the complex nature and potentially long run times of models capable of simulating hydrological processes (Christierson et al., 2012).

Conclusion

This study observed variable differences between the 11SCP and the 10,000 probabilistic projections depending on the decision criteria and projection used to evaluate options. This result was attributed to differences between the 11SCP and the 10,000 probabilistic projections, specifically the additional uncertainty considered by the latter. The interquartile and complete range of optimum outcomes suggested by the probabilistic projections were much larger compared

to the 11SCP, though the difference between the median optimum reservoir capacity using the 11SCP and probabilistic projections was comparably small compared to the difference between the maximum and minimum reservoir capacities respectively.

In addition, this study recorded variable differences between the probabilistic projections and 11SCP design reservoir capacities using different decision criteria and the median optimum reservoir capacity, considered here to be the “most likely” decision outcome. Design reservoir capacities calculated using certain decision criteria were more closely related to the median optimum reservoir capacity, specifically Laplace and to a lesser extent Minimax regret. Though it should be stressed that use of a single “most likely” projection in the manner described here should be avoided. Probabilistic projections present their own challenges and some of the current decision criteria are not ideal. However despite associated challenges, they remain popular because they are simple to implement and are founded on rational models which can be reasonably justified.

With regards to the sources of uncertainty posed in this study, the results would suggest that the largest source of uncertainty and the factor that has the greatest impact on irrigation reservoir design is the dataset used to evaluate options. Traditionally, decision makers have focussed their attention on emission scenario uncertainty. While differences between emission scenarios did contribute to the decision outcome, their impact was comparably small when compared with moving from the 11SCP to the 10,000 probabilistic projections (and the additional uncertainty considered) on irrigation reservoir design. These differences were most apparent where the decision maker exhibited a polarised risk appetite, as the extra uncertainty considered by the latter had a much larger impact where the maximum and minimum payoffs were used to compute design reservoir capacities. It is not clear whether the same is true for other assets in the field of water management and as a result this recommended for further work. This study did not consider the impact of other sources of uncertainties including modelling uncertainty, evapotranspiration uncertainty and statistical post-processing uncertainty associated with downscaling projections. The impact of these sources

of uncertainty has however been considered elsewhere and in greater detail and were generally found to contribute less uncertainty than the probabilistic projections themselves (Prudhomme and Davies, 2009; Kay and Davies, 2008; Kay et al., 2009; Bosshard et al., 2013).

With regards to sampling, it should be noted that sampling methods are ultimately confined by the available data. For the purpose of this study, as with most real-world applications, sampling is used to characterise the climate parameters using a small number projections to ease impact modelling. Sub-samples of the complete probabilistic dataset can then be fed into impact models to inform the decision outcome. However, in a non-linear system using the average or median values of the individual climate parameters does not necessarily give the average or median impact. The decision outcomes resulting from any sampling method, however complex will likely differ from that using the complete dataset. At which point the decision outcome becomes a function of the choice of sampling method and not the underlying dataset, with obvious implications.

Decision outcomes associated with certain methods, specifically Maximin and Maximax could not be effectively reproduced from sub-samples of the probabilistic dataset. This was despite trialling a number of different sampling methods, simple to complex, including Latin hypercube sampling. Latin hypercube sampling has previously been shown to be a suitable method for sub-sampling the UKCP09 probabilistic dataset. However, this study found that it did not improve the reproducibility of decision outcomes compared to using simplified sampling methods. Maximin and Maximax, and by extension Hurwicz should be strictly avoided when working with sub-samples of the complete probabilistic dataset given the limitations of the sampling methods. Laplace emerged as a viable decision criterion for use with sampling of the probabilistic dataset, showing strong reproducibility from different sub-samples. However, as with any decision criterion, Laplace may not appeal to decision maker's rational model and risk appetite and as a result other decision criteria may be sought.

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Appendix F Additional Results

F.1 Emission scenario uncertainty summary

Table F-1 Normalised relative impact score (0-100) attributable to emission scenario uncertainty and decision outcome of irrigation reservoirs (mm) and SUDS (m³) (pond shown) for the sites of Slaidburn and Woburn. Results obtained using 10,000 sample ensemble change factor dataset.

Irrigation reservoir – Slaidburn					SUDS (pond) – Slaidburn				
Laplace					Laplace				
Emission		L	M	H	Emission		L	M	H
		0	0	0			4600	4750	4850
L	0		0.00	0.00	L	4600		5.26	8.77
M	0	0.00		0.00	M	4750	5.26		3.51
H	0	0.00	0.00		H	4860	8.77	3.51	
Maximin					Maximin				
Emission		L	M	H	Emission		L	M	H
		0	0	0			3950	3950	3800
L	0		0.00	0.00	L	3950		0.00	5.26
M	0	0.00		0.00	M	3950	0.00		5.26
H	0	0.00	0.00		H	3800	5.26	5.26	
Maximax					Maximax				
Emission		L	M	H	Emission		L	M	H
		280	310	330			5550	5400	6250
L	280		8.11	13.51	L	5550		5.26	24.56
M	310	8.11		5.41	M	5400	5.26		29.82
H	330	13.51	5.41		H	6250	24.56	29.82	
Minimax regret					Minimax regret				
Emission		L	M	H	Emission		L	M	H
		100	120	140			4800	5000	5300
L	100		5.41	10.81	L	4800		7.02	17.54
M	120	5.41		5.41	M	5000	7.02		10.53
H	140	10.81	5.41		H	5300	17.54	10.53	
Hurwicz					Hurwicz				
Emission		L	M	H	Emission		L	M	H
		270	300	300			5000	5100	5700

L	270		8.11	8.11
M	300	8.11		0.00
H	300	8.11	0.00	
Green				
Emission		L	M	H
		0	0	0
L	0		0.00	0.00
M	0	0.00		0.00
H	0	0.00	0.00	

L	5000		3.51	24.56
M	5100	3.51		21.05
H	5700	24.56	21.05	
Green				
Emission		L	M	H
		4600	4700	4850
L	4600		3.51	8.77
M	4700	3.51		5.26
H	4850	8.77	5.26	

Irrigation reservoir – Woburn				
Laplace				
Emission		L	M	H
		360	380	390
L	360		5.41	8.11
M	380	5.41		2.70
H	390	8.11	2.70	
Maximin				
Emission		L	M	H
		0	0	0
L	0		0.00	0.00
M	0	0.00		0.00
H	0	0.00	0.00	
Maximax				
Emission		L	M	H
		530	580	620
L	530		13.51	24.32
M	580	13.51		10.81
H	620	24.32	10.81	
Minimax regret				
Emission		L	M	H
		380	420	440
L	380		10.81	16.22
M	420	10.81		5.41
H	440	16.22	5.41	

SUDS (pond) – Woburn				
Laplace				
Emission		L	M	H
		2450	2400	2550
L	2450		1.75	3.51
M	2400	1.75		5.26
H	2550	3.51	5.26	
Maximin				
Emission		L	M	H
		1800	1800	1800
L	1800		0.00	0.00
M	1800	0.00		0.00
H	1800	0.00	0.00	
Maximax				
Emission		L	M	H
		5050	4500	4800
L	5050		19.30	8.77
M	4500	19.30		10.53
H	4800	8.77	10.53	
Minimax regret				
Emission		L	M	H
		3600	3350	3650
L	3600		8.77	1.75
M	3350	8.77		10.53
H	3650	1.75	10.53	

Hurwicz					Hurwicz				
Emission		L	M	H	Emission		L	M	H
		510	540	570			4600	4450	4750
L	510		8.11	16.22	L	4600		5.26	5.26
M	540	8.11		8.11	M	4450	5.26		10.53
H	570	16.22	8.11		H	4750	5.26	10.53	
Green					Green				
Emission		L	M	H	Emission		L	M	H
		340	360	370			2350	2300	2500
L	340		5.41	8.11	L	2350		1.75	5.26
M	360	5.41		2.70		2300	1.75		7.02
H	370	8.11	2.70			2500	5.26	7.02	

F.2 UKCP09 sample ensemble uncertainty summary

Table F-2 Normalised relative impact score (0-100) attributable to UKCP09 sample ensemble uncertainty and decision outcome of irrigation reservoirs (mm) and SUDS (m³) (pond shown) for the sites of Slaidburn and Woburn. Results obtained using 10,000 sample ensemble change factor dataset and a median “most likely” decision outcome from economic analysis.

		Deterministic							
		Irrigation reservoir – Slaidburn				SUDS (pond) – Slaidburn			
		Emission	Low	Medium	High	Emission	Low	Medium	High
		Median decision outcome	0	0	0	Median decision outcome	4500	4650	4750
Probabilistic	Laplace	capacity (mm)	0	0	0	capacity (m ³)	4600	4750	4850
		norm diff.	0.00	0.00	0.00	norm diff.	3.51	3.51	3.51
	Maximin	capacity (mm)	0	0	0	capacity (m ³)	3950	3950	3800
		norm diff.	0.00	0.00	0.00	norm diff.	19.30	24.56	33.33
	Maximax	capacity (mm)	280	310	330	capacity (m ³)	5550	5400	6250
		norm diff.	75.68	83.78	89.19	norm diff.	36.84	26.32	52.63
	Minimax regret	capacity (mm)	100	120	140	capacity (m ³)	4800	5000	5300
		norm diff.	27.03	32.43	37.84	norm diff.	10.53	12.28	19.30
	Hurwicz	capacity (mm)	270	300	300	capacity (m ³)	5000	5100	5700
		norm diff.	72.97	81.08	81.08	norm diff.	17.54	15.79	33.33
	Green	capacity (mm)	0	0	0	capacity (m ³)	4600	4700	4850
		norm diff.	0.00	0.00	0.00	norm diff.	3.51	1.75	3.51

		Deterministic							
		Irrigation reservoir – Woburn				SUDS (pond) – Woburn			
		Emission	Low	Medium	High	Emission	Low	Medium	High
		Median decision outcome	320	340	340	Median decision outcome	2200	2200	2350
Probabilistic	Laplace	capacity (mm)	360	380	390	capacity (m ³)	2450	2400	2550
		norm diff.	10.81	10.81	13.51	norm diff.	8.77	7.02	7.02
	Maximin	capacity (mm)	0	0	0	capacity (m ³)	1800	1800	1800
		norm diff.	86.49	91.89	91.89	norm diff.	14.04	14.04	19.30
	Maximax	capacity (mm)	530	580	620	capacity (m ³)	5050	4500	4800
		norm diff.	56.76	64.86	75.68	norm diff.	100.00	80.70	85.96
	Minimax regret	capacity (mm)	380	420	440	capacity (m ³)	3600	3350	3650
		norm diff.	16.22	21.62	27.03	norm diff.	49.12	40.35	45.61
	Hurwicz	capacity (mm)	510	540	570	capacity (m ³)	4600	4450	4750
		norm diff.	51.35	54.05	62.16	norm diff.	84.21	78.95	84.21
	Green	capacity (mm)	340	360	370	capacity (m ³)	2350	2300	2500
		norm diff.	5.41	5.41	8.11	norm diff.	5.26	3.51	5.26

F.3 11SCP uncertainty summary

Table F-3 Normalised relative impact score (0-100) attributable to 11SCP uncertainty and decision outcome of irrigation reservoirs (mm) and SUDS (m³) (pond shown) for the sites of Slaidburn and Woburn. Results obtained using 10,000 sample ensemble change factor dataset and a median “most likely” decision outcome from economic analysis.

Decision criteria	Emission	Irrigation reservoir – Slaidburn				SUDS (pond) – Slaidburn		
		Probabilistic projections	11SCP	norm diff.		Probabilistic projections	11SCP	norm diff.
Laplace	Low	0	0	0.00		4600	4550	1.75
	Med	0	0	0.00		4750	4600	5.26
	High	0	0	0.00		4850	4750	3.51
Maximin	Low	0	0	0.00		3950	3800	5.26
	Med	0	0	0.00		3950	3800	5.26
	High	0	0	0.00		3800	3900	3.51
Maximax	Low	280	0	75.68		5550	5450	3.51
	Med	310	190	32.43		5400	5850	15.79
	High	330	200	35.14		6250	6150	3.51
Minimax regret	Low	100	0	27.03		4800	4900	3.51
	Med	120	0	32.43		5000	5200	7.02
	High	140	0	37.84		5300	5450	5.26
Hurwicz	Low	270	0	72.97		5000	5350	12.28
	Med	300	0	81.08		5100	5700	21.05
	High	300	0	81.08		5700	6000	10.53

		Irrigation reservoir – Woburn			SUDS (pond) – Woburn		
Decision criteria	Emission	Probabilistic projections	11SCP	norm diff.	Probabilistic projections	11SCP	norm diff.
Laplace	Low	360	280	21.62	2450	2050	14.04
	Med	380	280	27.03	2400	2050	12.28
	High	390	290	27.03	2550	2050	17.54
Maximin	Low	0	250	67.57	1800	1800	0.00
	Med	0	250	67.57	1800	1800	0.00
	High	0	250	67.57	1800	1800	0.00
Maximax	Low	530	300	62.16	5050	2200	100.00
	Med	580	300	75.68	4500	2150	82.46
	High	620	310	83.78	4800	2200	91.23
Minimax regret	Low	380	280	27.03	3600	2000	56.14
	Med	420	280	37.84	3350	2000	47.37
	High	440	290	40.54	3650	2000	57.89
Hurwicz	Low	510	290	59.46	4600	2050	89.47
	Med	540	280	70.27	4450	2100	82.46
	High	570	290	75.68	4750	2050	94.74

F.4 Sub-sampling uncertainty (using different sampling methods) summary

Table F-4 Normalised relative impact score (0-100) attributable to sub-sampling uncertainty (using different sampling methods) and decision outcome of irrigation reservoirs (mm) and SUDS (m3) (pond shown) for the sites of Slaidburn and Woburn. Results obtained using 10,000 sample ensemble change factor dataset and a median “most likely” decision outcome from economic analysis.

		Irrigation reservoir – Slaidburn					SUDS (pond) – Slaidburn				
		Decision outcome					Decision outcome				
Decision criteria	Emission	Complete dataset		SRS	OPT LHS	MAX LHS	Complete dataset		SRS	OPT LHS	MAX LHS
Laplace	Low	0	capacity (mm)	0	0	0	4600	capacity (m ³)	4580	4600	4600
			norm diff.	0.00	0.00	0.00		norm diff.	0.70	0.00	0.00
	Med	0	capacity (mm)	0	0	0	4750	capacity (m ³)	4750	4700	4700
			norm diff.	0.00	0.00	0.00		norm diff.	0.00	1.75	1.75
	High	0	capacity (mm)	0	0	0	4850	capacity (m ³)	4880	4880	4880
			norm diff.	0.00	0.00	0.00		norm diff.	1.05	1.05	1.05
Maximin	Low	0	capacity (mm)	0	0	0	3950	capacity (m ³)	4050	4100	4100
			norm diff.	0.00	0.00	0.00		norm diff.	3.51	5.26	5.26
	Med	0	capacity (mm)	0	0	0	3950	capacity (m ³)	4200	4200	4200
			norm diff.	0.00	0.00	0.00		norm diff.	8.77	8.77	8.77
	High	0	capacity (mm)	0	0	0	3800	capacity (m ³)	4200	4250	4250
			norm diff.	0.00	0.00	0.00		norm diff.	14.04	15.79	15.79
Maximax	Low	280	capacity (mm)	210	210	220	5550	capacity (m ³)	5150	5100	5100
			norm diff.	18.92	18.92	16.22		norm diff.	14.04	15.79	15.79
	Med	310	capacity (mm)	240	230	230	5400	capacity (m ³)	5450	5400	5400
			% diff.	18.92	21.62	21.62		norm diff.	1.75	0.00	0.00
	High	330	capacity (mm)	240	240	240	6250	capacity (m ³)	5700	5730	5730
			norm diff.	24.32	24.32	24.32		norm diff.	19.30	18.25	18.25
Minimax regret	Low	100	capacity (mm)	0	0	0	4800	capacity (m ³)	4650	4650	4650
			norm diff.	27.03	27.03	27.03		norm diff.	5.26	5.26	5.26
	Medium	120	capacity (mm)	0	0	0	5000	capacity (m ³)	4850	4800	4800
			norm diff.	32.43	32.43	32.43		norm diff.	5.26	7.02	7.02
	High	140	capacity (mm)	0	0	0	5300	capacity (m ³)	5030	5100	5100
			norm diff.	37.84	37.84	37.84		norm diff.	9.47	7.02	7.02
Hurwicz	Low	270	capacity (mm)	0	0	0	5000	capacity (m ³)	4750	4800	4800
			norm diff.	72.97	72.97	72.97		norm diff.	8.77	7.02	7.02
	Medium	300	capacity (mm)	0	0	0	5100	capacity (m ³)	5050	4950	4950
			norm diff.	81.08	81.08	81.08		norm diff.	1.75	5.26	5.26
	High	300	capacity (mm)	0	0	0	5700	capacity (m ³)	5200	5250	5250
			norm diff.	81.08	81.08	81.08		norm diff.	17.54	15.79	15.79
Green	Low	0	capacity (mm)	0	0	0	4600	capacity (m ³)	4530	4580	4580
			norm diff.	0.00	0.00	0.00		norm diff.	2.46	0.70	0.70

	Medium	0	capacity (mm)	0	0	0		4700	capacity (m³)	4700	4700	4700
			norm diff.	0.00	0.00	0.00			norm diff.	0.00	0.00	0.00
	High	0	capacity (mm)	0	0	0		4850	capacity (m³)	4800	4800	4800
			norm diff.	0.00	0.00	0.00			norm diff.	1.75	1.75	1.75

		Irrigation reservoir – Woburn					SUDS (pond) – Woburn				
		Decision outcome					Decision outcome				
Decision criteria	Emission	Complete dataset		SRS	OPT LHS	MAX LHS	Complete dataset		SRS	OPT LHS	MAX LHS
Laplace	Low	360	capacity (mm)	360	360	370	2450	capacity (m ³)	2430	2450	2350
			norm diff.	0.00	0.00	2.70		norm diff.	0.70	0.00	3.51
	Med	380	capacity (mm)	390	380	370	2400	capacity (m ³)	2400	2400	2400
			norm diff.	2.70	0.00	2.70		norm diff.	0.00	0.00	0.00
	High	390	capacity (mm)	390	390	390	2550	capacity (m ³)	2550	2600	2550
			norm diff.	0.00	0.00	0.00		norm diff.	0.00	1.75	0.00
Maximin	Low	0	capacity (mm)	0	210	210	1800	capacity (m ³)	1800	1800	1800
			norm diff.	0.00	56.76	56.76		norm diff.	0.00	0.00	0.00
	Med	0	capacity (mm)	220	220	240	1800	capacity (m ³)	1800	1800	1800
			norm diff.	59.46	59.46	64.86		norm diff.	0.00	0.00	0.00
	High	0	capacity (mm)	220	240	230	1800	capacity (m ³)	1850	1850	1850
			norm diff.	59.46	64.86	62.16		norm diff.	1.75	1.75	1.75
Maximax	Low	530	capacity (mm)	460	450	460	5050	capacity (m ³)	4130	3780	3800
			norm diff.	18.92	21.62	18.92		norm diff.	32.28	44.56	43.86
	Med	580	capacity (mm)	470	460	470	4500	capacity (m ³)	3600	3930	3680
			norm diff.	29.73	32.43	29.73		norm diff.	31.58	20.00	28.77
	High	620	capacity (mm)	480	510	490	4800	capacity (m ³)	3650	3900	3850
			norm diff.	37.84	29.73	35.14		norm diff.	40.35	31.58	33.33
Minimax regret	Low	380	capacity (mm)	360	390	380	3600	capacity (m ³)	3030	2880	2880
			norm diff.	5.41	2.70	0.00		norm diff.	20.00	25.26	25.26
	Medium	420	capacity (mm)	380	390	390	3350	capacity (m ³)	2800	2880	2830
			norm diff.	10.81	8.11	8.11		norm diff.	19.30	16.49	18.25
	High	440	capacity (mm)	390	420	410	3650	capacity (m ³)	2850	2980	2950
			norm diff.	13.51	5.41	8.11		norm diff.	28.07	23.51	24.56
Hurwicz	Low	510	capacity (mm)	420	410	420	4600	capacity (m ³)	3430	3150	3130
			norm diff.	24.32	27.03	24.32		norm diff.	41.05	50.88	51.58
	Medium	540	capacity (mm)	440	430	430	4450	capacity (m ³)	3100	3200	3130
			norm diff.	27.03	29.73	29.73		norm diff.	47.37	43.86	46.32
	High	570	capacity (mm)	430	470	440	4750	capacity (m ³)	3080	3280	3250
			norm diff.	37.84	27.03	35.14		norm diff.	58.60	51.58	52.63
Green	Low	340	capacity (mm)	340	340	340	2350	capacity (m ³)	2450	2450	2450
			norm diff.	0.00	0.00	0.00		norm diff.	3.51	3.51	3.51

	Medium	360	capacity (mm)	360	360	360		2300	capacity (m ³)	2450	2400	2450
			norm diff.	0.00	0.00	0.00			norm diff.	5.26	3.51	5.26
	High	370	capacity (mm)	370	380	370		2500	capacity (m ³)	2600	2650	2600
			norm diff.	0.00	2.70	0.00			norm diff.	3.51	5.26	3.51

F.5 Downscaling uncertainty summary

Table F-5 Normalised relative impact score (0-100) attributable to downscaling uncertainty and decision outcome of irrigation reservoirs (mm) and SUDS (m3) (pond shown) for the sites of Slaidburn and Woburn. Results obtained using 10,000 sample ensemble change factor dataset and a median “most likely” decision outcome from economic analysis.

•		Irrigation reservoir – Slaidburn			SUDS (pond) – Slaidburn		
Decision criteria	Emission	Change factor	Weather generator	norm diff.	Change factor	Weather generator	norm diff.
Laplace	Low	0	0	0.00	4600	4500	3.51
	Med	0	0	0.00	4750	4550	7.02
	High	0	0	0.00	4850	4600	8.77
Maximin	Low	0	0	0.00	3950	2950	35.09
	Med	0	0	0.00	3950	3300	22.81
	High	0	0	0.00	3800	3250	19.30
Maximax	Low	280	290	2.70	5550	6800	43.86
	Med	310	330	5.41	5400	6750	47.37
	High	330	260	18.92	6250	6800	19.30
Minimax regret	Low	100	120	5.41	4800	4900	3.51
	Med	120	140	5.41	5000	5200	7.02
	High	140	120	5.41	5300	5450	5.26
Hurwicz	Low	270	280	2.70	5000	5550	19.30
	Med	300	310	2.70	5100	6000	31.58
	High	300	260	10.81	5700	6350	22.81
Green	Low	0	0	0.00	4600	4450	5.26
	Med	0	0	0.00	4750	4550	7.02
	High	0	0	0.00	4850	4600	8.77

Decision criteria	Emission	Irrigation reservoir – Woburn				SUDS (pond) – Woburn		
		Change factor	Weather generator	norm diff.		Change factor	Weather generator	norm diff.
Laplace	Low	360	340	5.41		2450	2500	1.75
	Med	380	360	5.41		2400	2400	0.00
	High	390	370	5.41		2550	2500	1.75
Maximin	Low	0	0	0.00		1800	1800	0.00
	Med	0	0	0.00		1800	1800	0.00
	High	0	0	0.00		1800	1800	0.00
Maximax	Low	530	490	10.81		5050	4850	7.02
	Med	580	500	21.62		4500	5050	19.30
	High	620	550	18.92		4800	4150	22.81
Minimax regret	Low	380	370	2.70		3600	3150	15.79
	Med	420	390	8.11		3350	3300	1.75
	High	440	430	2.70		3650	3200	15.79
Hurwicz	Low	510	480	8.11		4600	3450	40.35
	Med	540	490	13.51		4450	2850	56.14
	High	570	550	5.41		4750	4050	24.56
Green	Low	360	330	8.11		2450	2450	0.00
	Med	380	340	10.81		2400	2350	1.75
	High	390	350	10.81		2550	2450	1.75